ELECTRICITY RELIABILITY: INDICES, COSTS, AND DECISION MAKING

BY

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TABLE OF CONTENTS

PAGE

ACKNOWLEDGEMENTS ii

ABSTRACT iv

CHAPTER

1 INTRODUCTION 1
  1.1 Purpose of Study 1
  1.2 Outline of Reliability Issues 2
  1.3 The Focus of This Study 3
  1.4 Summary of Conclusions 6

2 REVIEW OF THE LITERATURE 8
  2.1 Approaches to Reliability 9
  2.2 Studies of Reliability 12
  2.3 Empirical Studies of Reliability 23
  2.4 Directions for Research 28

3 RELIABILITY INDICES AND COST CHARACTERISTICS FOR ELECTRIC UTILITIES 29
  3.1 Reliability Indices 30
  3.2 Comparisons of Indices 36
  3.3 A Stylized Model of Utility Costs 45

4 MODELING THROUGH A SIMULATION APPROACH 57
  4.1 The Simulation Model 57

5 EMPIRICAL ESTIMATES OF THE ELECTRICITY COST OF RELIABILITY AND PRODUCTION 83
  5.1 Structure of the Model 83
  5.2 Econometric Results 87
  5.3 Comparison of Small Variation k-Mix and Large Variation k-Mix 98
  5.4 Price Setting with Reliability Constraint .. 100

6 CONCLUSIONS 104
  6.1 Summary 104
  6.2 Research Recommendations 106

LIST OF REFERENCES 108

BIOGRAPHICAL SKETCH 112

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Our increasing dependence on electricity brings awareness of the value of reliable service and the inconvenience and loss to consumers that may stem from interruptions to supply and load shedding. Since the cost of reliability is significant, decision-makers need to choose prices and capacity so as to balance additional benefits against the additional cost of reliability. Instead of trying to capture both the benefit and cost sides of alternative reliability levels, this research will concentrate on the understanding of the cost side and the implications of alternative reliability indices.

This study differs from previous economic studies in three respects. The reliability of power supply becomes an essential variable in the analysis of electricity costs. Two reliability indices widely used by engineers, loss of load probability, LOLP, and expected demand not served, ε(DNS), are considered here. The second contribution is that demand and supply are both treated as stochastic variables. The third aspect of the study warranting attention is the use of pseudo data. The numbers allow us to apply econometric estimation techniques to determine the cost of reliability.

Each of the indices has its own strengths and weaknesses, and cannot individually provide a complete description of outage patterns, nor of the value of lost consumption. The estimated indices are only significant in relative, rather than absolute terms.

Due to lack of sufficient and reliable data, pseudo data based on underlying engineering and economic considerations were used in this study. The model we propose is a set of two equations which consist of a reliability equation and a cost equation. A new concept, reliability elasticity of cost, was introduced to measure the sensitivity between cost and reliability. The statistical testing of estimated coefficients suggests that the ε(DNS) model provides the greatest explanatory power.

As to future research, we recommend three promising areas. They are the benefit side of reliability, interruptible service pricing, and generating unit size selection.

CHAPTER 1
INTRODUCTION

Electricity is a dominant feature of industrialized societies, serving as an input to industrial and commercial production and the major source of energy for the household sector. Consumption of electricity has consistently increased over the last few decades, doubling at least every ten years in developed countries. Utility managers are beginning base load construction programs which will increase capacity by 35 percent through the late 1980s. Since generating plants take a decade or more to plan and build, proper forecasting and the selection of appropriate reliability goals are key tasks facing utilities and regulators. Our increasing dependence on electricity brings awareness of the value of reliable service and the inconvenience and loss to consumers due to supply interruptions and load shedding. Yet we know that the cost of reliability is significant, requiring decision makers to choose prices and capacity to balance additional benefits against additional costs of reliability.

1.1 Purpose of Study

According to Electrical Power Research Institute (EPRI) studies (1978), almost one third of investment in power systems is utilized in standby plant and redundant transmission networks to achieve a higher reliability of supply. Due to the capital intensive nature of power systems, evaluation of reliability economics is of primary importance in importance in achieving optimum allocation of resources within the electricity supply industry. Furthermore, the issue of reliability had arisen out of a concern on the part of the public and of regulators that utilities may be incurring excessive costs for reliability. This concern has come at a time when utilities are seeking to curb expenditures, and we might well be concerned that utilities are cutting so deeply into their construction programs that over the long-run the reliability of electric service will be severely jeopardized.

From the engineering standpoint, system reliability is one of the major factors in the planning, design, and operation of power systems, since reliability criteria have a major impact on the requirement of new facilities and system operating security. The criteria ultimately affect the quality of service and the rates customers pay. Utilities are therefore under pressure to make more precise evaluations of reliability criteria and the associated costs and benefits.

1.2 Outline of Reliability Issues

Power system reliability is one aspect of the wider topic of the effectiveness of energy supply systems as a whole. Some of the interrelated issues include

1. Concepts of reliability
    a. Behavioral implications--risk indices in planning and operation
    b. Technical analysis--methodologies for evaluating reliability
    c. Scheduling algorithms for maintenance and repair
2. Load forecasting and demand uncertainties
3. Uncertainties in primary energy availability

4. Load management and reliability
    a. Peak load or time-of-use pricing
    b. Interruptible service pricing
    c. Direct load control
5. Determination of optimum reliability
    a. Data collection and preparation for decision-makers
    b. Cost of reliability and its estimation
    c. Worth (benefit) of reliability and its estimation
6. Environmental and socio-economic consequences of non-price rationing (such as blackouts)
    a. Defining and quantifying the kinds of environmental, economic, and social effects
    b. Determining what measures might be taken by utility companies and their customers during electricity shortages to avoid costs
7. Costs and benefits of over and under capacity in the generation of electric power (Are the costs of being underprepared for future electric demands significantly greater than the costs of being overprepared?)

1.3 The Focus of This Study

Cost-benefit analysis and its employment in the planning of the power system has not advanced in the way it has in other public services (e.g., transportation), partly due to the great difficulty in obtaining comprehensive assessments and measures of reliability at the generation system level, down to outage due to distribution system failure. Still more difficult is the assessment and inconvenience of lost consumer valuations due to interruptions. It is possible, however, to assess the contribution of different schemes toward the continuity of supply and to choose the one with the maximum contribution within "reasonable cost."

The problem still remains as to determining the reasonable cost and of choosing a reliability index that is conceptually sound.

Systems planners do not aim at a completely uninterruptible supply, although the constraint or reliability criterion is usually taken as a given rather than analyzed as a determinant of revenue requirements. Ideally, we search for a point of "optimum reliability"; that is, point E in Figure 1-1. Two factors must be balanced: the reliability marginal cost curve to the electric utility industry and the marginal benefit of reliability. The latter concept depends on the marginal cost of interruptions to the consumer (marginal value of the demand not served). As construction and financial costs have increased, measurement of the costs and benefits of reliability have become increasingly important. Estimation of the cost curve is conceptually straightforward and shall be the focus here. Even this one-sided approach requires the resolution of some extremely complex issues.

As to the marginal benefit of reliability, one analytical approach involves measuring the resulting reduction in consumer surplus loss: outage costs are reflected in the effects on the production of final goods and services in various sectors. Conceptually, a marginal benefit curve of reliability can be constructed, but few economists have addressed this issue.

Instead of trying to capture both benefit and costs sides of alternative reliability levels, this research will sharpen our understanding of the cost of reliability and implications of alternative reliability indices. In Chapter 3, we first discuss the meanings and implications of alternative reliability indices, including loss of load probability

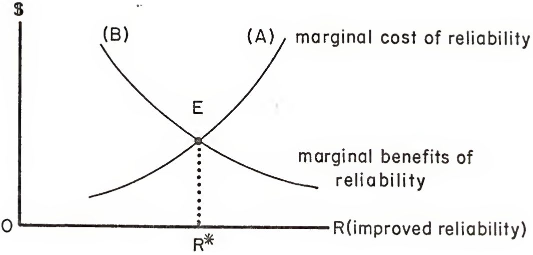

$
(B)
(A)
marginal cost of reliability
E
marginal benefits of reliability
O
R*
R(improved reliability)

Figure 1-1. Determination of Optimal Reliability

and expected demand not served. The cost characteristics of the utility industry are then reviewed to facilitate the development of a highly stylized characterization of these costs.

The framework is extended in the next chapter to simulate the electricity systems. The simulations allow the estimation of cost of reliability equations. In Chapter 5, a cost model for the estimation of reliability costs is presented. The econometric results are then presented and discussed.

1.4 Summary of Conclusions

Since the cost of reliability is significant, decision makers need to choose prices and capacity so as to balance additional benefits against the additional cost of reliability. Instead of trying to capture both the benefit and cost sides of alternative reliability levels, this research will concentrate on understanding the cost side and the implications of alternative reliability indices.

This study differs from previous economic studies in three respects:

1) The reliability of power supply is an essential variable in the analysis of electricity costs. Two reliability indices widely used by engineers, LOLP and ε(DNS), are considered here.

2) Demand and supply are both treated as stochastic variables.

3) Pseudo data are used to apply econometric estimation techniques to determine the cost of reliability.

Each of the indices has its own strengths and weaknesses and cannot individually provide a complete description of outage pattern nor of the value of lost consumption. The estimated indices are only significant in relative, rather than absolute terms. Since the indices are generally neither comparable nor consistent, they yield different rankings of systems by different reliability indices.

Due to lack of sufficient and reliable data, pseudo data based on underlying engineering and economic considerations were used in this study. A simulation model to generate such data is presented in Chapter 4. We then use alternative regression models to estimate the cost of reliability in Chapter 5.

The model we proposed is a set of two equations which consist of a reliability equation and a cost equation, appearing in a recursive system. A new concept, reliability elasticity of cost, was introduced to measure the sensitivity of cost to different reliability levels. The statistical testing of estimated coefficients suggests that the ε(DNS) model provides the best estimate.

As to future research, we recommend three promising areas: the benefit side of reliability, interruptible service pricing, and generating unit size selection.

CHAPTER 2
REVIEW OF THE LITERATURE

One of the difficult problems faced by electric supply system planners is that of deciding how far they are justified in increasing the investment in their equipment to improve service reliability. Both engineers and economists are interested in this important issue. Naturally, engineering studies are engineering-technical efficiency oriented. This line of research is best represented by the work of Roy Billington and Robert Sullivan. Economic studies, in contrast, are economic efficiency-oriented and use the concept of economic value. Illustrative studies are those by Brown and Johnson, Crew and Kleindorfer, and Munasinghe and Gellerson. In these economic studies, there are two different approaches to determining an optimal reliability level. A detailed discussion of these approaches will be presented in this chapter.

The analysis of peak load pricing under the deterministic case, which has now become standard, produces the rule that prices should equal marginal opportunity costs or the price necessary to restrict demand to capacity. The first study to introduce elements of risk into the analysis was by Brown and Johnson (1969). In their model, the social welfare function that is maximized is the algebraic difference between expected willingness to pay and expected cost. They concluded that the optimal price will always be lower and, with linear demand, the optimal output will generally be higher than their counterparts in the riskless model of traditional theory, regardless of the manner in which the disturbance term enters the analysis.

2.1 Approaches to Reliability

Generally, there are two different approaches to determining the optimal reliability level, the welfare-maximum approach and the Munasinghe/Gellerson benefit/cost (B/C) approach. We can summarize the complex analysis of the welfare-maximum approach in a very simplified form as follows: Economic efficiency would be maximized if price is set equal to marginal cost, determining the capacity level and reliability level in the process. The B/C approach optimizes the reliability level by comparing the social benefits and costs of change in power system reliability. These costs (supply side) can be determined from engineering considerations, such as technical constraints regarding capacity availability. On the demand side, the benefits to electricity users consist of cost savings from averted power failure, which may be measured by the disruption of the output streams owing to idle input factors and spoilage.

As can be seen in Table 2-1, there are two major differences between the two approaches. First, in the welfare-maximum approach, electricity is treated as a good which directly provides consumers with satisfaction. Therefore, outage costs are measured primarily in terms of the resulting reduction in consumer surplus (plus rationing costs in the case of Crew and Kleindorfer). However, in the Munasinghe and Gellerson B/C approach, electricity is viewed as being an intermediate

Table 2-1. Approaches to Reliability

Models	Key Assumptions	Conclusions
A. Welfare Maximization Approach	Maximizing net welfare by satisfying joint first order conditions with respect to prices and capacity.	
1. Brown and Johnson (1969)	1-1 $D = f(p, \mu)$, where D = Demand and μ = disturbance term.	Optimal price: $p = b$, where b = operating cost.
	1-2 Costlessly rationing.	
	1-3 Welfare function is defined as: $E\{w\} = E\{CS + TR - TC\}$.	
	1-4 Demand has been assumed independent of the reliability of service.	
2. Meyer (1975)	2-1 To analyze the effects of risk averse behavior (i.e., demand of reliable service) by introducing constraints as follows: prob $(D(p)\mu \leq z) \geq \varepsilon$, where z = capacity level and ε = reliability requirement.	Optimal price: $p = b$.
3. Crew and Kleindorfer (1978)	3-1 Reliability constraint may be thought of as a surrogate for rationing cost. It is clear that the higher the required reliability level is, the lower the expected rationing cost will be.	Optimal price: $p = b$.

(Continued on the following page.)

Table 2-1, continued

Models	Key Assumptions	Conclusions
4. Sherman and Visscher (1978)	4-1 Imposing a break-even constraint: $E\{TR\} = E\{TC\}$.	Second-best price: $\frac{p-b}{p} = \frac{\lambda}{1+\lambda} \cdot \frac{1}{E(\eta)}$, where λ = Lagrangian multiplier, $E(\eta)$ = Expected price elasticity.
5. Tschirhart (1979)	5-1 Adding reliability as an argument of the demand function.	Optimal price: $p = b$.
B. Benefit and Cost Approach	Optimizing reliability, given fixed price, by weighing the costs and benefits associated with alternative levels of reliability.	Optimum reliability is reached when marginal benefit of reliability (outage cost savings) = marginal cost of reliability (supply cost).
C. Empirical Study		
Crew and Kleindorfer (1980)	$R = f(S_{t-k}, L_t, I_t, E_t, N_t, H_t, C_t, G_t, A_t)$ where R = Reserve margin, S = Reported rate of return on equity, L = Load factor, I = Imports of power, E = Exports of power, N = Proportion of nuclear capacity, H = Proportion of hydro-capacity, C = Proportion of fossil capacity, G = Proportion of internal combustion capacity, and A = average plant size.	a. AJ effects are much more complicated under uncertainty. b. The result describing the relationships between reliability and AJ effects is inconclusive.

product which is used to produce final goods that are demanded by consumers. Outage costs are measured in terms of the effects on the production of final goods and services in various sectors of the economy. These approaches are not mutually exclusive; each can throw light on this complex topic.

A second difference between the approaches, given a rationing or load shedding scheme, is that the welfare approach maximizes net welfare by satisfying joint first order conditions with respect to prices and capacity. Partial approaches which attempt to optimize reliability in the presence of given prices cannot ensure that resulting net benefits are minimized. However, in practice, electricity tariffs are often not readily subject to change in the short run. Therefore, M&G developed a method of optimizing reliability by weighing the costs and benefits associated with alternative levels of reliability, given fixed prices. Once the optimal reliability level is determined in the first round, tariffs can be revised to reflect any changes in the cost of supplying electricity implied by the new reliability level. With this new level of tariffs and the resulting revised demand forecast, reliability can be re-optimized. The process can be continued until it determines the internally consistent combination of tariffs and reliability that maximizes the net social benefits of supplying electricity.

2.2 Studies of Reliability

Much of the literature of public enterprise pricing ignores stochastic phenomena affecting demand and available capacity. For example, the problem of peak load pricing for public utilities has been thoroughly explored under conditions of certainty. As mentioned at the beginning of this chapter, the analysis of the deterministic case, which has now become standard, produces the rule that price should equal whichever is the higher, either marginal running costs or the price necessary to restrict demand to capacity. A paper by Brown and Johnson (1969), hereinafter referred to as BJ, first introduced elements of risk into the analysis.

BJ extended the problem to situations where demand is subject to a random disturbance. It was assumed that a producer is directed to maximize expected social welfare and must announce a price and capacity output before actual demand is known. Leland (1972) suggested that the electric power industry is a good example of price setting, where prices are set before demand (D) is known and then output is adjusted to meet demand. However, when demand exceeds capacity, no further output can be produced. In the short run, the utility cannot adjust capacity to meet demand since capacity adjustments require too much time. This point underscores the issues of electricity reliability which can arise.

In the BJ model, the arguments of the welfare function to be maximized include the expected value of willingness to pay, the expected value of variable cost, and the capacity cost known with certainty. We can define the welfare function as follows:

$$\begin{aligned} E(W) &= E(\text{willingness to pay}) - E(\text{average variable cost} \cdot \text{sales}) \\ &\quad - E(\text{capacity cost}) \\ &= E(\text{consumers' surplus} + \text{total revenue} - \text{total cost}). \qquad (2\text{-}1) \end{aligned}$$

Consumers' surplus refers to the usual consumers' surplus triangle under the demand curve. As can be seen in Figure 2-1, when quantity demanded (given P_0) exceeds capacity (Z), part of the triangle is not attained. Any portion of the triangle beyond the capacity level is

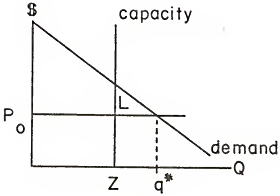


Figure 2-1. Lost Consumer Surplus

lost, since demand in this region is not satisfied. This portion, denoted by L, represents lost consumer surplus. Here Z represents capacity and P_0 is the going rate. This definition of L requires that consumers are costlessly ranked according to their willingness to pay. When demand exceeds capacity, those consumers with the highest valuation are served first. In practice, ranking consumers is not a costless activity, so the lost consumer surplus when demand is not served may be greater than L.

Figure 2-2 illustrates two other ways to ration the excess demand, where q* is energy demanded. The demand not served is q* - Z. Assume that the aggregate demand consists of the sum of n identical demands. Let $(q^* - Z) = (1/n)q^*$. Thus, a fraction of customers are blacked out and they lose their ability to consume. Their loss, area M, is greater than L, the minimum lost consumer surplus. On the other hand, the greatest loss in consumer surplus would involve area N, and the highest valued uses would go unserved. A blackout affecting a special set of consumers might involve such a situation. The index involving lost quantities does not necessarily reflect lost values. Engineers use demand not served as a reliability index. Economists, however, would stress that the economic value of the demand not served is the key concept for evaluating alternative pricing/capacity choices.

As demonstrated by BJ, when E(W) is maximized with respect to price, the first order conditions for maximization of the welfare function indicate that price should equal short run marginal operating cost. The optimal price is lower under the risk model than it is in the traditional deterministic model (where $p = b + \beta$). Given that the optimal

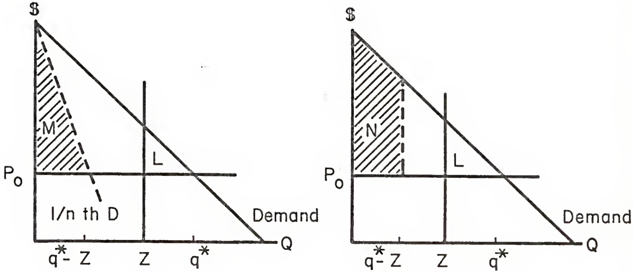


Figure 2-2. Consumer Surplus Versus Demand Not Served

price is below the riskless optimal price, the law of demand would seem to suggest that optimal output will be greater than equilibrium output in the riskless model (Brown and Johnson, 1969).

The reason that prices equal operating cost can be clearly explained by using the diagram (Figure 2-3) in Tschirhart's paper (1979), where four demand curves are drawn for four values of the disturbance term (μ_i). These values of 0.5, 0.71, 1, and 2 enter into the demand function in multiplicative form. Since capacity is chosen ex ante, total capacity cost is essentially a fixed cost (sunk cost) when demand becomes known. For demand curve 0.5x, price = b is clearly the welfare maximizing price since operating cost b is covered and consumers' surplus is at a maximum. This price also applies for any demand curve up to curve 0.71x.

For demand curve 2x, if the lowest valued users can be costlessly identified and not served, any price between zero and p'' will yield the same welfare. Note that the distribution of welfare between producers and consumers will vary. Prices near zero for demand curve 2x will require more rationing, with excess demand becoming smaller when the price is getting closer to p''. This reasoning also applies for any demand beyond curve 0.71x. Thus, price plays a major role in the determination of service reliability. Tschirhart concludes that in the short run, P* is also the optimum but not the unique price for all demands beyond 0.71x. Thus, P* was selected because it is the optimum for all four cases. The argument crucially relies on the assumptions that those who value the service least are the first to be cut off when rationing is necessary, and that rationing is costless.

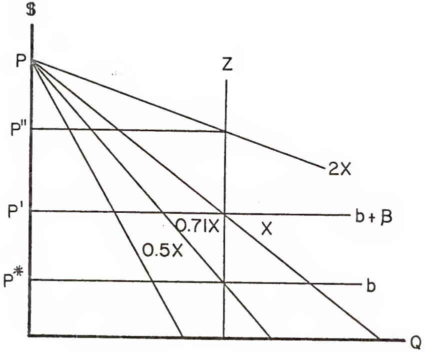


Figure 2-3. Comparison of Optimal Pricing

Meyer (1975) and Crew and Kleindorfer (1978) extended the BJ model in order to rectify this inadequacy. In the former, a chance constraint on reliability is used, while in the latter, rationing costs are introduced. A chance-constrained programming formulation allows one to directly introduce a "reliability of service" or risk constraint and analyze the effects of risk averse behavior (i.e., demand of reliable service) without the explicit introduction of a utility function. In addition, it provides a formal basis for analyzing the issue raised by BJ (1970) when they state: "To price so high that there is rarely (never?) excess demand implies persistent excess supply (idle capacity) and an ad hoc decision by the public utility to remove the risk of failure. . . ." This approach is used by Meyer to obtain prices that are sufficiently high to meet specified standards of system reliability. The procedure is to add the following constraints to the problem:

$$P\{x_i(p_i)\mu_i \leq z\} \geq \varepsilon_i > 0, \tag{2-2}$$

where P indicates probability. $x_i(p_i)\mu_i$ is the stochastic demand function; z is the capacity level. The value of the ε_i reflects the stringency of system reliability requirements: a larger ε_i implies more stringent requirements. Also ε_i can be considered as an LOLP index. This chance constraint approach to excess demand is representative of current practice in some countries. For instance, planners in the U.S. electric power generation system tend to use a "one-day-in-ten year" loss-of-load probability as a reliability target.

BJ (1970) acknowledged the cost of excess demand, vis. rationing, in a reply to comments by Salkever (1970) and Turvey (1970), but they made no attempt to add this cost to the model. Suppose a penalty cost of ϕ is assessed for each unit of excess demand; ϕ can be thought of as the cost of rationing, including the cost of ranking consumers. If the excess demand only occurs during the peak load period, rationing costs are a peak load phenomenon.

Crew and Kleindorfer (1978), hereinafter referred to as CK, examined the problems of optimal pricing and capacity planning when diverse plant types of differing cost characteristics are available and when demand is stochastic. They concluded that the existence of a diverse technology (i.e., multiple plant types) gives rise to a system-wide marginal cost curve which is upward sloping (this is a natural consequence of a diverse technology), since plants are used in order of their equipment's running efficiency. Accordingly, marginal cost pricing is desirable under peak load pricing with uncertainty. And on the other hand, capacity planning involves deciding the reliability of supplies. When capacity is exceeded, certain 'rationing costs' arise in allocating output to consumers. The inclusion of such rationing costs in the analysis highlights the trade-off between losses due to insufficient capacity and costs of additional capacity. Recognition of rationing costs tends to further enhance the desirability of peak load pricing to smooth peak consumption and decrease the frequency of forced rationing. That is, the presence of rationing costs leads to an even more pronounced peak load pricing policy.

CK also pointed out in their paper that the BJ framework had neglected the important issue of reliability and that imposing explicit constraints limiting the probability of excess demand might significantly alter their results. CK's results suggest maximizing the traditional welfare function subject to reliability constraints. It is clear that the higher the required reliability level, the lower the expected rationing cost will be. Thus, the reliability constraint may be regarded as a constraint on expected rationing costs and may be thought of as a surrogate for rationing costs. The presence of such rationing costs then induces optimal behavior close to that implied by the usual deterministic analysis. In particular, peak load pricing continues to be optimal in the stochastic case since marginal rationing costs are higher in peak periods.

Sherman and Visscher (1978), hereinafter referred to as SV, developed second best pricing rules so that the firm could remain financially viable. As Meyer indicated in his paper (1975), "optimal price equals marginal (and average variable) cost, thus a firm's net profits will always be negative." When demand is stochastic, the expected welfare-maximizing price does not produce sufficient revenue to cover costs. So by imposing a break-even constraint, SV demonstrated how risk will influence optimal second best prices. The constrained welfare maximizer raises peak price above marginal costs by the greatest amount, but only by an amount sufficient to break even. When demand is random, there is no assurance that any price or capacity level chosen before demand is known will clear the market once demand is revealed. For if prices are set high enough to break even on average, capacity will go unutilized whenever demand is unusually low.

Tschirhart (1979) relaxed the implicit assumption that demand is independent of the reliability of service. The addition of reliability in the demand function brings the models of public utilities with stochastic demand closer to a position of being able to assess accurately the welfare implications of joint pricing and capacity choices. Reliability is an important aspect of utility service that has not been fully appreciated. In particular, Tschirhart indicated that an increase in price may improve welfare via an improvement in reliability, when reliability is allowed as an argument (exogenous variable) in the demand function. In Chapter 5 we investigate the cost of reliability as an endogenous variable.

Turning from theoretical studies to more applied analyses of reliability, we note that the estimation of outage cost and supply cost is necessary to achieve optimal decisions. The term "outage costs" is used to encompass all the economic costs suffered by society when the supply of electricity is not perfectly reliable. Electric power supply shortages are exhibited in various ways, ranging from power surges, frequency variation, and voltage level drops (brownouts) to load shedding and complete interruptions of supply (blackouts). These effects impose certain economic costs on consumers. Mohan Munasinghe (1979) developed a theoretical framework to estimate the residential outage costs.

The application of an optimization technique for reliability level requires estimation of electricity supply costs. Munasinghe concludes that no generalized production function model derived from neoclassical economic theory could hope to capture the detailed characteristics of a physical power system. In particular, sector-wide production functions based on cross section or pooled data are generally appropriate to determine historical trends in the economics of electric power sector evolution. However, such functions do not represent a given system accurately, because the estimates remain oriented in the past rather than the present or future (i.e., they do not incorporate current input prices or units coming on-line). An engineering model used in the design and planning of a system incorporates future system supply costs when the reliability level is to be optimized. Of course the process of system planning and determining electricity supply costs is usually complicated by several practical difficulties, including resolving uncertainties in the demand projections, errors in the cost estimates, technological changes, construction delays, and environmental constraints.

2.3 Empirical Studies of Reliability

The optimum level of reliability is easier to define theoretically than to measure in practice. Its computation requires two sets of data:

1. A set which shows how the incremental costs (∂C) respond to additional reliability of supply (∂R), that is, $\frac{\partial C}{\partial R}$.

2. Another set of data showing to what extent consumer loss (∂L) is spared and alleviated through increased reliability (∂R), that is, $-\frac{\partial L}{\partial R}$ (this value is negative because increased reliability causes less loss).

No previous empirical studies have established these components with accuracy. Appropriate data are unavailable at either the micro (individual firm) or sectoral level. Tschirhart (1980) indicated that empirical work on demand estimation with reliability as an argument would be difficult in most countries since, historically, reliability has been on the order of 99 percent with little variation. His analysis pointed out, however, that there may be welfare gains available through decreases in reliability because over-reliable service is simply too costly. Consumers, if given a chance, may opt for lower reliabilities if accompanied by lower prices. A reliability of 75 percent would undoubtedly be unacceptably low, but a "one-day-in-one-year" (99.73 percent) or a "one-day-in-five-year" (99.95 percent) loss of load probability may be a better target than the "one-day-in-ten-year" (99.97 percent) estimate.

Sant (1979) suggested that cost functions be modeled to include both yearly output and the temporal distribution of that output (i.e., load factor). Otherwise, he suggested, the estimate of electricity costs would be biased due to generation mix effects. He still failed to stress that the reliability of electricity should also be included in the cost equation, although the load factor could be viewed as a proxy for how reliability would be affected by peak KW demands.

Michael Telson (1975) examined the cost of providing an incremental amount of production through installing an additional amount of generation to a system which was built at the loss of load probability criterion of one-day-in-ten-years, and found that society would be paying at least 208 times the revenue of the additional energy produced by the "incremental" megawatt. He also examined the welfare losses caused by not having that energy and concluded that we could at most attribute a factor of forty to this value. Thus, his calculations suggest that one-day-in-ten-year loss of load probability criterion is too conservative. He recommends reducing generation system reliability target levels to perhaps a five-day-in-ten-year criterion. It is also interesting to note that the United States seems to have had the highest electric service reliability experience in the world. He also quoted the U.S. experience as 99.98 percent reliability in terms of energy sales and a 1.75-hour loss per customer per year. The equivalent figures for the next highest countries, France and Great Britain, were 99.93 percent and six hours and 99.80 percent and 17.5 hours, respectively. As the cost of reliability rises, it will become more attractive to reduce reliability target levels and to devise pricing and/or rationing schemes to reduce the peak loads which account for a great part of an electric system's unreliability, unless the benefits of reliability increase by the same amount. However, note that modern microprocessor metering technology and interruptible rate structures make it possible to reduce the capacity requirement for given stochastic demands.

Crew and Kleindorfer (1979) used ordinary least-squares (OLSQ) to estimate a reliability equation. The proposed equation form was as follows (all variables are measured in the current period t except for s which was lagged k periods):

$$R_t = f(S_{t-k}, L_t, I_t, E_t, N_t, H_t, C_t, G_t, A_t).$$

Data from 39 utility companies covered a period from 1971 to 1978, and consisted of the following:

S = Reported rate of return on total assets

L = Load factor (a measure of utilization of a system)

I = Imports of power

E = Exports of power

N = Proportion of nuclear capacity

H = Proportion of hydro capacity

C = Proportion of fossil capacity

G = Proportion of internal combustion capacity

A = Average plant size

$R = \frac{\text{Capacity - peak}}{\text{Capacity}}$.

This is the only published paper to discuss the estimation of the reliability equation. Also, only one reliability index, reserve margin, was used in this analysis.

Their concern was mainly with the effects of regulation on potential overcapitalization and reliability. Crew and Kleindorfer concluded that the inclusion of reliability in the model offers no straightforward way to test the AJ effect under uncertainty. Their use of ex post reserve margin as the reliability index severely limits their analysis. Furthermore, by definition, installed capacity is used to calculate reserve margin; however, installed capacity is nonstochastic. Both demand and supply are stochastic variables in the calculation of LOLP and ε(DNS). Taking another approach to the problem of cost, James Griffen (1977) modeled a long run electric power generation cost function with pseudo data. He used a process model to generate the data. The electric power process model used in his paper consisted of 73 linear equations with 98 process activities. The process model is a linear programming problem, with the following translog cost function model as follows:

$$\ln C = \ln\alpha_0 + \ln Q + \sum_{i=1}^{8} \alpha_i p_i + \tfrac{1}{2} \sum_{i=1}^{8} \cdot \sum_{i=1}^{8} \beta_{ij} (\ln p_i) \ln p_j ,$$

where C is total cost, Q is output, and p_i refers to the eight input prices. Surprisingly, he did not include any reliability variables in the cost model.

According to Griffen, his pseudo data approach offered numerous advantages compared to conventional time series particularly in that they avoid multicollinearity, a limited sample range, and inadequate technical and environmental detail. He noted that the pseudo data approach is subject to certain caveats and limitations. The value of the pseudo data approach ultimately rests on the quality and completeness of the underlying process model, which is typically difficult for non-engineers to validate. Pseudo data are also subject to both measurement errors and errors regarding assumed behavioral parameters.

Smith and Vaughan (1979) pointed out that the results derived from Griffen's exercise are only as good as the information in the underlying process analysis model, including the detail with which the technology is represented. They used three process analysis models to analyze iron and steel production. Their findings suggest that Griffen's warning concerning the possible limitations of pseudo data was well founded.

According to Maddala and Roberts (1981), it is not clear that the way Griffen went about condensing the technical information in the process model is very useful because Griffen's pseudo data approach deals with an attempt at a single-equation summarization of data generated from a complex process analysis model (i.e., a linear programming problem was set up and solved). However, they did agree to Griffen's claim that one cannot study the effects of new technology and environmental policies with the help of time-series data, and that one has to look at more micro-engineering data to get an idea of these effects.

In this study, due to lack of significant and sufficient empirical data, we will simulate a process model to generate pseudo data for empirical tests. This approach promises to yield insights into system reliability. Before discussing the particular prices, technological demand parameters, and the respective stochastic components, we need to have a clear idea of how various reliability indices are related. Such detailed discussion will be presented in Chapter 3.

2.4 Directions for Research

One of the management options which we believed needed further research was the use of pricing policies. Pricing was considered to be an important facet of shortage prevention and management. Research should cover the effectiveness of various pricing schemes and potential draw-backs in regulatory-determined rate structures for utilities. The equipment and administrative costs of implementing and managing alternative price schemes were also considered an area in need of further research. For example, new metering devices would be required for residential customers for the introduction of time-of-day pricing. The costs of such meters need to be taken into account if such rate structures are to be used in a cost-effective manner.

In addition, models should be developed to assess the socioeconomic impacts of an electricity shortage. The development of appropriate criteria for optimizing reliability is also an important issue in need of more research. Finally, sound process models are needed to generate pseudo data for facilitating current research and to provide a guideline for future data collection.

CHAPTER 3
RELIABILITY INDICES AND COST CHARACTERISTICS FOR ELECTRIC UTILITIES

The term reliability is used in an engineering sense to indicate quality of constancy of service. A number of indices have been introduced in reliability theory to characterize reliability, such as Effective Reserve Margin (RM), Loss of Load Probability (LOLP), Expected Demand not Served (ε(DNS)), Expected Energy not Served (ε(ENS)), Expected Loss of Load (XLOL), Frequency and Duration (FAD), and Safety Margin (S). Just as a four-firm concentration index cannot fully represent all the dimensions of market power, no single reliability index is likely to be an ideal measure of the multi-dimensional quality variable called "reliable service." For instance, we find electricity systems planners moving from the traditional reserve margin index to a loss-of-load-probability index for investment planning purposes. Given the amount of resources involved, the topic is important both to utility companies and regulators.

This chapter presents mathematical definitions and concise analyses of various reliability indices, including the advantages and disadvantages of each index. Their links to cost are especially important since when evaluating the reliability of a number of alternative power plans, it is necessary to estimate the cost associated with a particular plan. Thus, we will also review the cost characteristics of electric utilities in the later sections of this chapter.

3.1 Reliability Indices

3.1.1 Effective Reserve Margin (RM)

Perhaps the most commonly used index in the press is the reserve margin, although reported numbers are ex post (after stochastic demand and supply have been realized). This index in its ex ante form can be defined as

$$RM = \frac{IC - Le}{IC}, \tag{3-1}$$

where

IC = installed capacity, and

Le = effective load,

$= L + \Sigma L_{oi}$.

Again, L = expected load (ex ante), and

L_{oi} = the random outage load of the i^{th} unit.

The rationale for this calculation is that the firm should provide for such factors as unit forced outages, scheduled outages for maintenance, and load forecast uncertainty, when relating the effective load to the available capacity. Sometimes the ex post, or realized reserve margin, is used as an index of reliability, but this version of the index is invalid as a planning tool.

3.1.2 Loss of Load Probability (LOLP)

LOLP is defined as the probability that effective load exceeds installed capacity (IC) of a particular proposed generation system. At present, the LOLP criterion is commonly used for generation planning. Since system failure is most often defined in terms of inability to meet the daily peak load, the LOLP is usually computed not as a strict probability but rather as an expectation: This index may be interpreted as the average number of days over a long period during which the daily peak demand is expected to exceed the available generating capacity. For example, the probability that the load will exceed the installed capacity of 100 MW of the generation system is 0.02981; that is, LOLP = 0.02981. Because the number 0.02981 is unclear, it is common to convert the LOLP into so many hours per week or days per year, because the LOLP can be interpreted as the percentage of time the load is expected to exceed the installed capacity. Here, the load is interpreted as including outages or down-time for the capacity.

$$\text{LOLP (in hours/week)} = 0.02981 \times 168$$
$$= 5.008 \text{ hours/week,}$$

or

$$\text{LOLP (in days/year)} = 0.02981 \times 365 \text{ days/year}$$
$$= 10.88 \text{ days/year.}$$

The target LOLP frequently used for planning the United States is one-day-in-ten-years, but the rationale for this target is unclear. As was noted earlier, Telson, among others, is critical of this goal (1975).

3.1.3 Expected Demand Not Served (ε(DNS))

In order to understand the next index, expected demand not served, we need to introduce the effective load probability density function. Suppose a continuous random variable, effective load (denoted by X), has a normal distribution, with a mean of 50 MW and a standard deviation of 15 MW. Assume that we have 70 MW of installed capacity. What is the probability that the effective load X will be more than 70 MW (installed capacity)? By definition, this probability is LOLP. Also, this probability is the area under the normal probability distribution more than 70 MW, as shown in the shaded area A of Figure 3-1(A).

The first step in finding the area A is to calculate the Z-score corresponding to the measurement 70 MW. We calculate

$$Z = \frac{X - u}{\sigma}$$

$$= \frac{70 - 50}{15} = 1.33.$$

Thus, the measurement, 70 MW, is 1.33 standard deviations away from the mean, 50 MW. By looking at the Z-table, we find

$$p(50 \leq x \leq 70) = 0.4082$$

$$= \text{area B}.$$

The desired probability is

$$p(Z > 1.33) = 0.5 - B$$

$$= 0.5 - 0.4082$$

$$= 0.0918 = \text{LOLP at 70 MW}.$$

We can repeat the above procedure to derive the effective load probability distribution as shown in Figure 3-1(B). For example, the probability that the effective load will exceed 50 MW is 0.5.

Expected demand not served (ε(DNS)) is beginning to see widespread use because of its obvious economical significance, and is defined as the expected value of instantaneous KW demand in excess of installed capacity, IC. In order to explain this concept, we refer to Figure 3-2. By definition, if (ε(DNS)) = 0, all units are 100 percent reliable and

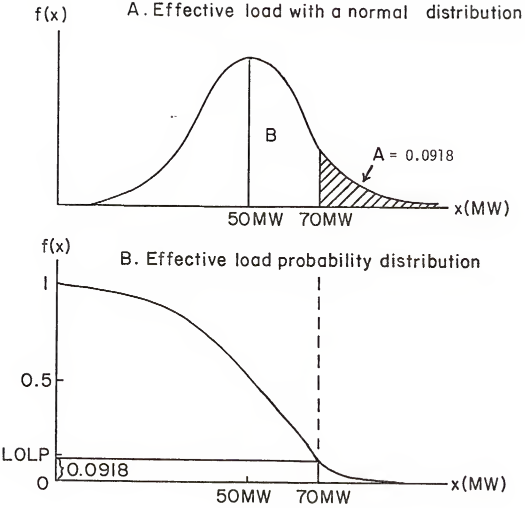


Figure 3-1. Random Loads and the Effective Load Probability Distribution

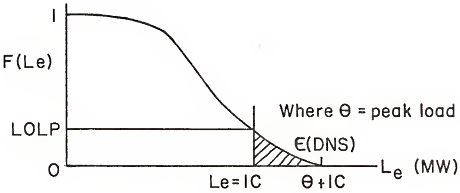


Figure 3-2. Typical Effective Load Probability Distribution

capacity is greater than the maximum expected MW demand. The mathematical definition of (ε(DNS)) is

$$\varepsilon(DNS) = \int_{Le=IC}^{\theta+IC} F(Le)dLe, \qquad (3\text{-}2)$$

which is the area under the curve in the above figure from Le = IC to θ + IC, as indicated.

3.1.4 Expected Energy Not Served (ε(ENS))

If Equation 3-2 is multiplied by T, the time period represented by F(Le), the (ε(ENS)) results:

$$(\varepsilon(ENS)) = T \int_{Le=IC}^{\theta+IC} F(Le)\, dLe \qquad (3\text{-}3)$$

This concept is more closely related to economic rather than engineering features in that the amount (although not the dollar value) of consumption is being measured. The unit of measurement for ε(DNS) is MW, while the measure for ε(ENS) is MWH.

3.1.5 Expected Loss of Load (XLOL)

The LOLP is often supplemented by the expected loss of load index, which indicates the expected magnitude of the unsupplied load, given that a failure has occurred; therefore, XLOL is a conditional expectation. That is,

$$[\text{load - supply/load - supply} > 0] = \varepsilon(DNS)/LOLP\ . \qquad (3\text{-}4)$$

3.1.6 Frequency and Duration (FAD)

The expected frequency or mean recurrence time between outages and their expected duration represent two other reliability indices. These indices are used widely in transmission and distribution system planning, but rather infrequently in generation studies, and can be categorized as follows:

- i) Frequencies, such as the average number of failures per unit time, and
- ii) Mean duration, such as the mean time to the first failure and the mean time between failures.

3.2 Comparisons of Indices

Table 3-1 summarizes commonly used reliability indices. The definitions and units of measurement serve to illustrate the wide range of concepts used by practitioners. Several general points about measures of reliability should be noted. First of all, each of the indices has its strengths and weaknesses, and cannot individually provide a complete description of outage patterns. For example, although LOLP is a measure of the probability of system failure, the LOLP does not indicate the expected magnitude of the load lost during such a contingency. In contrast, the XLOL provides the expected magnitude, but neither the probability nor the average duration of an outage. Like the LOLP, the FAD measure also does not indicate the mean size of the failure, but because the FAD indices are specified at the load point or particular point of consumption, the number of affected customers may be deduced.

Second, the methods of computation and their interpretation may vary. Although they are often related in well-defined ways, the indices are generally neither comparable, nor consistent: they could yield different rankings of systems by reliability level. Similarly, rankings by cost over the planning horizon can be expected to differ, although establishing a baseline for making comparisons is no simple task.

Table 3-1. Summary of Commonly used Reliability Indices

	Index	Definition	Units of Measurement
1.	Effective reserve margin	$RM = \frac{IC - Le}{IC}$.	%
2.	Loss of load probability (LOLP)	LOLP = probability (Le > IC).	$0 \leq LOLP \leq 1$
3.	Expected demand not served $\{\varepsilon(DNS)\}$	$\varepsilon(DNS) = \int_{Le=IC}^{\theta+IC} F(Le)d(Le)$.	MW (or KW)
4.	Expected energy not served $\{\varepsilon(ENS)\}$	$\varepsilon(ENS) = T \cdot \varepsilon(DNS)$.	MWH (or KWH)
5.	Expected loss of load (XLOL)	$XLOL = \varepsilon(\text{load-supply}/\text{load-supply}>0)$ $= \varepsilon(DNS)/LOLP$.	MW (or KW)
6.	Frequency, duration of failure	Number of failures per year; average duration	#/year; hours

Notations: IC = Installed Capacity, Le = effective load, t = time (hours), and θ = peak load.

Third, the estimated indices may be much more significant in a relative rather than an absolute sense. Reliability indices are usually computed as predictors of long run average system performance, but they do not reflect actual experience well. That is, the difference between actual and predicted values can be substantial. The range depends on the extent of potential forecast errors, in terms of unit failures and electricity demand.

Fourth, the LOLP index is more significant in the mind of the system planner, but from the consumer's standpoint, the FAD is more significant. The FAD index is easier to understand, and production and consumption activities are directly related to the duration and frequency of outage. Given particular FAD patterns, the ε(DNS) index may be of greatest interest to the economist, since it raises two important economic issues: the opportunity cost of outage and the supply cost of eliminating outage.

Lastly, the implications of alternative indices warrant attention. Let us begin by reproducing the right corner of Figure 3-3 (see Figure 3-4). Again, the shaded area represents the ε(DNS), and the intercept of the vertical axis represents the corresponding LOLP. We can consider three illustrative cases.

Case A. Both Curve A and Curve B in Figure 3-4 represent different magnitudes of ε(DNS). That is, ε(DNS) of Curve A is greater than the ε(DNS) of Curve B. However, Curve A and Curve B have the same LOLP denoted by point L. Can we claim that two curves have the same reliability? In order to answer this question, it is necessary to introduce

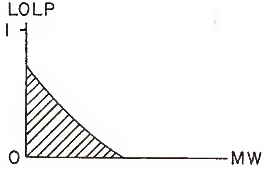


Figure 3-3. LOLP and ε(DNS)

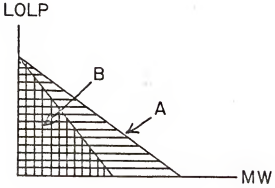


Figure 3-4. Same LOLP vs. Different ε(DNS)

a new concept, "generalized" reliability, denoted by R*. R* is a function of all reliability indices. That is $R^* (R_1, R_2, \ldots, R_n)$. For example R_1 = LOLP, $R_2 = \varepsilon$(DNS), etc.

For the convenience of comparison, we define

R_A^* = Generalized reliability preference of Curve A, and

R_B^* = Generalized reliability preference of Curve B.

In this particular example

$R_B^* > R_A^*$: B is more reliable than A, where

R_{A1}= LOLP of Curve A,

R_{B1}= LOLP of Curve B,

R_{A2}= ε(DNS) of Curve A, and

R_{B2}= ε(DNS) of Curve B.

In Figure 3-4, $R_A^*(R_{A1}, R_{A2}) < R_B^*(R_{B1}, R_{B2})$. This is simply because $R_{A1} = R_{B1}$, $R_{B2} < R_{A2}$. Thus, the answer for Case A is that Curve B is more reliable than Curve A.

Case B. Both Curve A and Curve B, shown in Figure 3-5, represent the same magnitude of ε(DNS). However, they have different LOLP indices, denoted by point L and point M respectively. Again, can we claim that both Curve A and Curve B have the same reliability; by the same decision criterion: $R_{A1} > R_{B1}$ and $R_{A2} = R_{B2}$, so $R_A^*(R_{A1}, R_{A2}) < R_B^*(R_{B1}, R_{B2})$. In other words, Curve B is more reliable than Curve A, if these are the only two dimensions of reliability that matter. If we bring XLOL into the above function (and drop LOLP), we have

$XLOL_B > XLOL_A$,

since XLOL = εDNS/LOLP. Thus, $XLOL_A$ is the area under the A curve divided by the LOLP: Since the areas are the same but $LOLP_A$ is greater

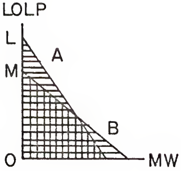


Figure 3-5. Different LOLP vs. Same ε(DNS)

than $LOLP_B$, $XLOL_A$ is less than $XLOL_B$. Thus, we would conclude that curve A is more reliable than curve B.

Case C. Even though both Curve A and Curve B, shown in Figure 3-6, have the same magnitude of LOLP and $\varepsilon(DNS)$, it is still inappropriate to claim that both Curve A and Curve B have the same reliability. For instance, $\varepsilon(DNS)$ of curve B might be caused by just a one-shot loss. However, $\varepsilon(DNS)$ of curve A is accumulated by many small losses. Thus, both curves probably represent different outage frequency and duration. Also, both curves might have different cost implications. For example, the power generating system of curve B could consist of two generators (80MW and 20MW), and the power generating system of curve A could consist of five generators (5MW, 10MW, 15MW, 25MW, and 45MW). Since the generating systems have different capacity mixes, they have different cost structures, even if they have the same total capacity. The latter might cost a little more due to more generators in the capacity mix, resulting in a reduction in scale economies.

In conclusion, each of the reliability indices has its own strengths and weaknesses and cannot individually give a complete description of power system reliability. They could yield different rankings of the system by reliability level. We need to consider all indices when evaluating power system plans, and the weight assigned to each index in the generalized reliability function should also be taken into consideration. From the standpoint of public policy, the weights ought to reflect the implications of the indices for the economic value of lost consumption. Chao (1983) takes a step in this direction using some specific consumer surplus loss functions.

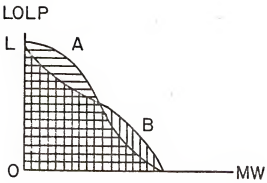


Figure 3-6. Same LOLP vs. Same ε(DNS)

3.3 A Stylized Model of Utility Costs

Capacity costs, energy costs, and timing of additions are three major elements which influence the overall cost of expansion plans. For simplicity, we will use a highly stylized model of an electric utility to generate a set of data reflecting the engineering/economic trade-off relating short-run production costs and reliability. The numbers are meant to illustrate production constraints and to provide a data base for testing the applicability of traditional econometric cost functions. The total annualized capacity cost of unit β_i is defined as follows:

$$\beta_i^* = F_i cc_i k_i, \text{ and} \tag{3-5}$$

$$\beta_i = \frac{\beta_i^*(1{,}000)}{Q_p} = \frac{(F_i cc_i k_i)(1{,}000)}{Q_p}, \tag{3-6}$$

where

cc_i = capacity acquisition cost per MW of unit i,

k_i = capacity in MW of unit i,

Q_p = peak demand (KW x peak hours),

$cc_i \cdot k_i$ = total actual acquisition cost (\$/MW),

F_i = fixed charge rate (covers taxes, depreciation, and cost of capital),

β^* = total annualized capacity cost (\$/MW), and

$\beta = \frac{\beta_i^*}{Q_p}$ = capacity cost per peak KWH.

By definition, the fixed charge rate associated with investment in unit i is the annual expense associated with the investment expressed as a percentage of initial investment (i.e., $cc_i k_i$). It reflects taxes, depreciation, and the allowed return on investment.

The energy cost associated with unit i can be defined as

$$b_i = f_i + m_i,$$

where

f_i = fuel cost per KWH,

m_i = operation and maintenance cost per KWH, and

b_i = energy cost per KWH of unit i.

Because future fuel costs are very difficult to predict, utilities must consider a range of fuel costs and fuel types in evaluating expansion alternatives. Typical operating and maintenance costs for various plant types are obtained through engineering studies.

We can easily define total production cost in terms of equations 3-6 and 3-7:

$$TC = \beta Q_p + b(Q_o + Q_p), \qquad (3\text{-}7)$$

where

Q_p = peak demand, and

Q_o = off-peak demand.

Both sides of Equation 3-7 can be divided by the expected value of the annual energy produced by unit i, denoted by $\varepsilon(E_i)$, then the total cost might be expressed in mils/KWH or \$/MWH, which is often convenient when comparing different plants types. Engineers define $\varepsilon(E_i)$ as follows:

$$\begin{aligned} \varepsilon(E_i) &= 8{,}760\ \varepsilon(CF_i)k \\ &\simeq 8{,}760\ CF_i\ k\ , \end{aligned}$$

where

CF_i = capacity factor.

Clearly, the timing of investment via the addition of a new unit can drastically change the operation of existing units, thus changing total system cost.

3.3.1 Cost (capacity cost and fuel cost) and Mix of Generating Plant

For simplicity, only two kinds of generating units are considered: gas turbines and base load steam plants. Figure 3-7 is a graph of the (annualized) total cost per megawatt of installed capacity, that is, capital cost plus operating cost, plotted as a function of the numbers of hours of operation. Gas turbines have lower capital costs (represented by the intercept β_1), but higher fuel costs (as indicated by the slope, b_1, of the operating cost curve) than the steam plant. The cost characteristic of these units has been simplified for convenience of analysis by assuming fixed values of β_1, β_2, b_1, and b_2. As the upper diagram shows, from the economic point of view, gas turbines are more expensive than base load units if they are to be used more than H hours a year. The lower diagram for load curve A indicates that it would be economical to serve the bottom OF megawatts of load (i.e., the base load) with steam units and the upper FG megawatts of load (i.e., the peak load) with gas turbines. For load curve B, the choice rule for capacity mix is changed.

In practice, there are many kinds of generating units including nuclear, coal and oil-fired steam, gas turbines, and conventional and pumped-storage hydro. The units have characteristics varying by type and by size. All would have to be taken into account, when generation additions were being considered to meet future load growth. However, the basic principle of selecting units with lower capital costs but higher operating costs for peaking purposes generally holds true.

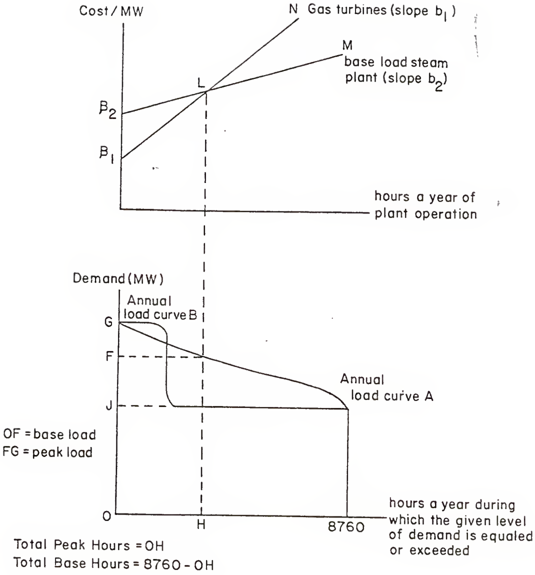


Figure 3-7. Cost Relationships

3.3.2 Average Costs of Base Load and Peak Load Energy

It must not be thought that every energy kilowatt-hour costs the same to produce, even if generated by the same plant. This can be seen from the following purely illustrative example. Assume that the load is supplied by a single plant of 750 MW capacity. Further assume that the generation costs from this plant are \$10.5 million per annum (capacity cost) plus 2.5 mills per KWH (variable). The load duration curve may be conceived of as consisting of a very large number of thin horizontal elements such as that shown (not to scale) in Figure 3-8. As the thickness of this element is one kilowatt, it bears 1/750,000th of the capacity cost (\$10.5 million) or \$14/KW per annum. The energy generated by this particular kilowatt during the year will be h kilowatt-hours, where h is the breadth of the element in hours. Hence the capacity costs to the element may be expressed as

$$\text{Capacity cost per KWH in mills} = \frac{14 \times 1{,}000}{h}, \quad (\$1 = 1{,}000 \text{ mills}).$$

To this must be added the variable cost of 2.5 mills per KWH so that the average costs of generating this element of energy will be

$$\left(\frac{14{,}000}{h} + 2.5\right) \text{ mills per KWH.}$$

Assume that the particular element illustrated in Figure 3-8 corresponds to a load of 440 MW at which level the value of h is 2,800 hours. The average cost of generating this element of energy will therefore be

$$AFC + AVC = AC$$

$$\frac{14{,}000}{2{,}800} + 2.5 = 7.5 \text{ mils/KWH,}$$

where

AFC = average fixed cost, and

AVC = average variable cost.

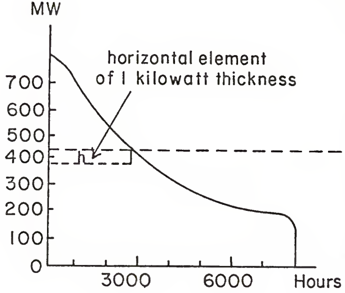


Figure 3-8. Annual Duration Curve

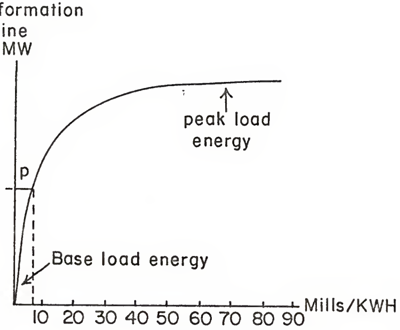


Figure 3-9. Average Cost for Various Loads

This figure is represented by p in Figure 3-9, which shows on the horizontal axis the average costs of each kilowatt element of load from the base load to the extreme peak. Note that the value of h is getting smaller as the load moves from base load to the peak load.

In practice, the load will be supplied by several plants. From the standpoint of efficiency, it is desirable that the base load, the intermediate loads, and the peak loads be supplied by different types of plants with different cost characteristics.

3.3.3 Numerical Calculations of Capacity Cost (β)

In Figure 3-10, we assume that the total actual acquisition cost ($cc_i k_i$) is \$109.5/MW and the fixed charge rate (F_i) is 10 percent. By Equation (3-5)

$$\beta_i^* = 10\% \times \$109.5 = \$10.95/\text{MW}.$$

Further assume under uniform pricing that peak KWH demand per day (12 hrs. peak, 12 hrs. off-peak) is 1,000 KWH, and off-peak KWH demand per day = 500 KWH. Thus, 1,000 KWH/12 hrs. is needed for capacity (i.e., 83 1/3 KW to meet hourly peak demand per day). Furthermore, annual KWH peak consumption (Q_p) = 83 1/3 KW x 12 hrs. x 365 days = 365,000 KWH, and annual KWH off-peak consumption (Q_o) = 41 2/3 KW x 12 hrs. x 365 days = 182,500 KWH. In other words, annual total consumption is 547,500 KWH/yr.

Capacity cost per peak KWH can be derived from Equation (3-6),

$$\beta_i = \frac{\$10.95 \times 1000}{365{,}000} = 3¢/\text{KWH (peak)}.$$

Also, average capacity charge per KWH under uniform pricing is

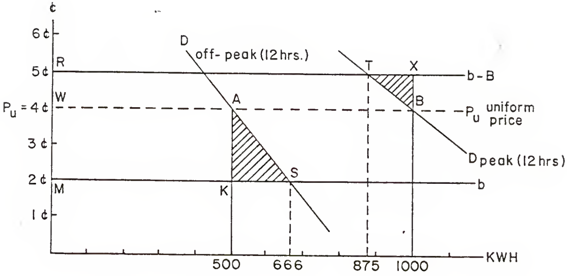


Figure 3-10. Uniform Pricing vs. Peak Load Pricing

\$10,950/547,500 (i.e., 2¢/KWH). Note that the shaded area in Figure 3-11 shows short run misallocations (efficiency losses) under uniform pricing:

(i) TXB represents the loss due to under-pricing for peak customers, and

(ii) ΔAKS represents the loss due to over-pricing for off-peak customers.

3.3.4 Reliability and Peak Load Pricing

As shown in Figure 3-10, peak quantity demanded (1,000 KW per 12 hours) under uniform pricing has been reduced. The reduction of peak demand implies the increase of reliability and the decrease of outage rate. Also, there are two welfare gains. One is capacity saving (greater than consumer valuation of the output), represented by ΔTXB. The other is the increase of consumer surplus (which is greater than the increase in fuel costs), represented by ΔAKS.

3.3.5 Plant Mix under Diverse Technology

Regarding the optimal prices, Crew (1979) reveals the result that prices are set at marginal cost. (See notes for detailed mathematical proofs.) There are two major conclusions regarding optimal prices and optimal plant mix. Under diverse technology

(i) optimal price (p_1 = off peak price, p_2 = peak price)

$$p_2 = b_2 + \beta_2,$$

$$p_1 = (2b_1 + \beta_1) - (b_2 + \beta_2),$$

where

$$b_1 < p_1 < b_2 < b_2 + \beta_2 = p_2 < b_1 + \beta_1 .$$

The introduction of a more diverse technology leads to lower

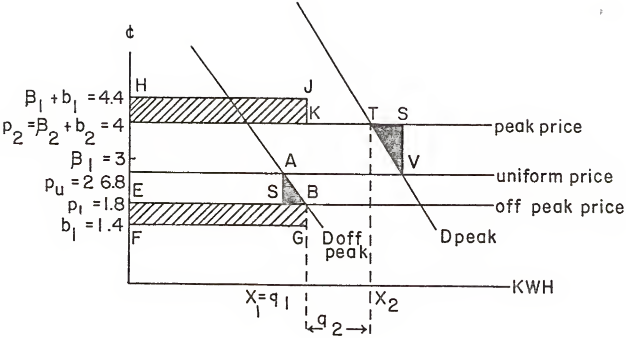


Figure 3-11. Price and Plant Mix Under Diverse Technology

Note: β_1 = capacity cost per day
β_2 = capacity cost per day

peak-period efficient prices and higher off-peak efficient prices.

(ii) optimal plant mix (x_1 = off-peak demand, x_2 = peak demand, q_1 = Plant 1 output, and q_2 = Plant 2 output).

The cost conditions for m technologies are as follows:

$$\beta_1 > \beta_2 \ . \ . \ . > \beta_m > 0 \ ,$$

$$0 < b_1 < \ . \ . \ . < b_m \ .$$

Capacity is installed and operated in order of increasing operating cost. In particular, Plant 1 is used in every period to meet all demand. If m = 2, Plant 2 is filling the remaining demand. Thus,

$q_1 = x_1$, and $q_2 = x_2 - x_1$.

To illustrate, assume a plant mix consisting of two plants with per unit operating costs (b_1 and b_2) and daily per unit capacity costs (β_1 and β_2),

where

$b_1 = 1.4$, $b_2 = 2$, $\beta_1 = 3$, and $\beta_2 = 2$.

The demand functions are

$p_1 = 100^{(-X1/4)}$

$p_2 = 200 - 10X_2$.

The welfare optimal prices are

$p_1 = (2b_1 + \beta_1) - (b_2 + \beta_2) = 1.8$, and

$p_2 = (b_2 + \beta_2) = 4$.

Then we can derive x_1, x_2 from the demand function: $x_1 = 16.07$ and $x_2 = 19.60$.

It is straightforward to show that the optimal amounts of each plant (q_1 and q_2) to construct are

$q_1 = x_1$ and $q_2 = x_2 - x_1$,

with Plant 1 being operated to full capacity in both periods and Plant 2 being used only in the peak period.

In Figure 3-11, there are several shaded areas, each with specific economic interpretations:

(i) ΔTSV represents net improvement in peak period allocative efficiency (capacity savings which outweigh customer valuation of the lost output),

(ii) ΔABC represents net consumer surplus gain (after taking the transfer into account),

(iii) Peak price is 4¢/KWH; however, the cost of peak electricity production by Plant 1 is 4.4¢/KWH. The total loss is represented by p_2HJK. In contrast, off-peak price is 1.8¢/KWH. Up to an output of X_1, the off-peak cost is 1.4¢/KWH; FEBG represents total revenues greater than costs (quasi-rents earned from this consumption).

This model of diverse technology is used in the next chapter to generate cost data relating production and reliability. The concepts developed here establish the basis for formulating a process model which permits us to generate pseudo data to be used in an econometric analysis of costs.

CHAPTER 4
MODELING THROUGH A SIMULATION APPROACH

This study differs from previous studies in three respects. The first is that the reliability of power supply becomes an essential variable in the analysis of electricity costs. In most previous economic literature, reserve margin and the probability that demand does not exceed capacity are the only reliability indices used. However, two other reliability indices widely employed by engineers, Loss of Load Probability (LOLP) and Expected Demand not Served ε(DNS), are considered here.

The second contribution we will attempt to make involves treating both demand and supply as stochastic variables. Most previous studies consider demand as the only stochastic element, which severely limits analysis, especially in the context of unit outages. The third aspect of the study warranting attention is the use of pseudo-data (the results of a set of simulations). The numbers allow us to apply econometric techniques to determine the cost of reliability.

4.1 The Simulation Model (Process Model)

The result of this simulation test will facilitate several economic analyses. First, the data permit an econometric estimation of a cost of reliability equation:

$$C = f(R, TKWH, K, u), \tag{4-1}$$

$$R = g(pKWH, K, v), \tag{4-2}$$

where

C = total cost,

R = reliability,

TKWH = total electricity consumption,

pKWH = peak load electricity consumption,

K = capacity generation mix, and

u, v = disturbance terms.

In addition, the data allow us to determine a set of prices which will maximize the net benefit subject to reaching a given level of reliability (measured in terms of a particular index).

4.1.1 Variables and Parameters in the Model

Before getting into the detailed mechanism of the simulation model, a flow chart, Figure 4-1, is presented to summarize the interrelation among relevant variables and parameters. This flowchart will enable readers to follow the general framework of this simulation.

Note that the analysis can be divided into two areas. The first area involves a simulation model (process model) which is designed to generate pseudo data based on underlying economic and engineering relationships. These pseudo data are generated by a well-specified model. Then we use alternative regression models to estimate the cost of reliability. The econometric tests will be presented in the next chapter. For now, we identify the underlying assumptions. Assume that demand has the following functional form:

$$D_i(p_i, u_i) = f(p_i) + u_i \tag{4-3}$$

where

p = price, and

u = disturbance term.

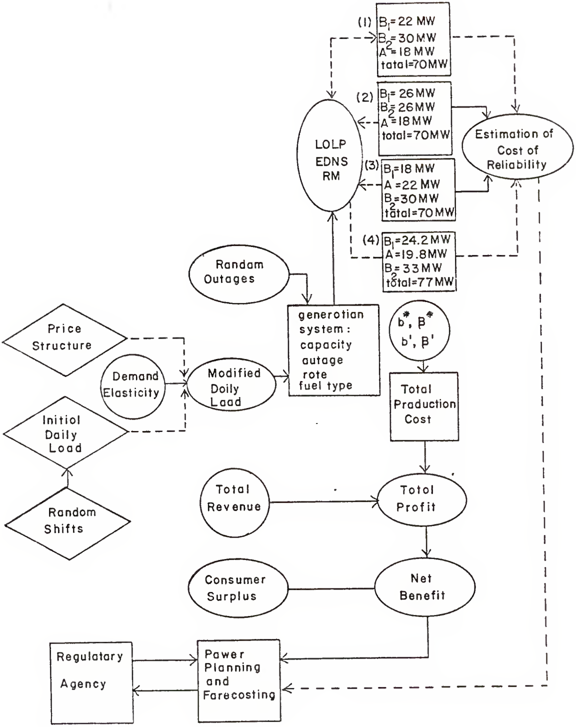


Figure 4-1. Flowchart of Simulation Model

Demand is subject to random fluctuations so it is stochastic. The utility company (producer) cannot choose a particular price and be certain as to what the load response (demand) will be. We assume reference demands for the peak and off-peak periods. Instead of the riskless relationship $D = D(p)$, the electricity producer is confronted with $D = D(p, u)$. Of course, demand for electricity can be a function of electricity price (base rate and fuel adjustment), per capita income, population, and other factors. For simplicity, we assume price is the only independent variable. Also, both peak and off-peak demands are in linear form:

$$D^*(p^*, u^*) = a^* + d^*p^* + u^* \tag{4-3a}$$

$$D'(p', u') = a' + d'p' + u' \tag{4-3b}$$

where

D^* = peak demand = q^*,

D' = off-peak demand = q'',

p^* = peak price,

p' = off-peak price, and

u^*, u' = disturbance terms.

We let total cost be a separable function of capacity cost, and of fuel and maintenance cost. These two costs per unit of output are defined as β and b, respectively.

This type of cost function has been used extensively in the literature on peak-load pricing*. We further assume that the generation capacity is divisible for running purposes. Also, this is a closed utility model, so we do not consider power pooling. For simplicity, this simulation only considers fuel cost and capacity. We also assume that the base unit is used to meet demand during the peak period, and the peak unit is used to fill the remaining peak demand. Accordingly, the total cost equations for firm peak and off-peak demands under two technologies can be formulated as follows:

---

*The average capacity cost per unit of output assumes that the plant is fully utilized. Brown, G., and Johnson, B. M., American Economic Review, Vol. 59 (March 1969), pp. 119-128.

$$C^* = (b' + \beta')q_b^* + (b^* + \beta^*)q_p^* = \text{peak total cost}, \tag{4-4a}$$

$$C' = b'q' = \text{off-peak total cost}, \tag{4-4b}$$

where

C^* = peak total cost,

C' = off-peak total cost,

β^* = peak-unit capacity cost (\$/KWH),

β' = base-unit capacity cost (\$/KWH),

b^* = peak fuel cost (\$/KWH),

b' = base-load fuel cost (\$/KWH),

q_b^* = peak demand supplied by base unit under peak load pricing,

q_p^* = peak demand supplied by peak unit under peak load pricing,

q^* = peak demand $= q_b^* + q_p^*$, and

q' = off-peak demand.

The following social welfare function can now be employed. The expected value of welfare is

$$E(W) = E(TR + CS - TC), \tag{4-5}$$

where

TR = total revenue,

CS = consumer surplus, and

TC = total cost.

By Equation 4-3, our demand function in general form is $q = D(P, \mu)$. In general, the demand curve can also be written as $P = \psi(q, \varepsilon)$. Thus, $E(W) = E(TR + CS - TC)$ can be written as

$$E(W) = (p^*q^* - (\int_0^{q^*} (q^*, \varepsilon^*)dq^* - p^*q^*) - C^*) + (p'q' - (\int_0^{q^*}(q', \varepsilon')dq' - p'q') - C') \qquad (4\text{-}5a)$$

where

p^* = peak price,

p' = off-peak price, and

μ, ε = disturbance terms.

A practical question can now be posed: would it be socially efficient to switch from uniform pricing to time-of-day pricing? Our general approach to this problem may be treated as the problem of maximizing a net welfare function of the following form:

$$W_1 = TR_1 + CS_1 - TC_1, \qquad (4\text{-}6)$$

$$W_2 = TR_2 + CS_2 - TC_2, \qquad (4\text{-}7)$$

$$W_2 - W_1 = (TR_2 - TR_1) - (TC_2 - TC_1) + (CS_2 - CS_1), \qquad (4\text{-}8)$$

$$\Delta W = \Delta\pi + \Delta CS, \qquad (4\text{-}9)$$

$$TC_1 = C^{**} + C'', \qquad (4\text{-}6a)$$

$$TC_2 = C^* + C', \qquad (4\text{-}7a)$$

where subscript 1 represents the uniform pricing case, and subscript 2 represents the time-of-day pricing case.

$c^{**} = (b' + \beta')q_b^{**} + (b^* + \beta^*)q_p^{**}$,

$c'' = b'q''$,

q_b^{**} = peak demand supplied by base unit under uniform pricing,

q^{**} = peak demand supplied by peak unit under uniform pricing, and

q'' = off-peak demand under uniform pricing.

The term ΔW represents net welfare returns (net benefit) under perfect rationing (costless rationing according to willingness to pay). In addition, $\Delta\pi$ represents the profit change between uniform price and time-of-day prices (i.e., peak price and off-peak price). The term ΔCS consists of the net consumer surplus changes. One change is from the difference between peak price and base price (uniform price) while the other is from the difference between off-peak price and base price.

We can also incorporate a reliability constraint into the above analytical framework. In addition, the derivation of an optimal set of time-of-day prices can be obtained through the maximization process of the above welfare function, subject to reaching a given level of reliability.

The general form of the reliability equation can be written as follows:

$$R = g(D^*, K) + v, \tag{4-10}$$

where

R = reliability index (LOLP or ε(DNS) or RM),

K = capacity generation mix,

D^* = peak load, and

v = disturbance term.

Capacity generation mix refers to different combinations of generators. Each of the generators has its own capability, fuel type, and outage rate. Thus, different capacity mixes imply different generation reliability. To calculate LOLP or ε(DNS), two items of information are required:

(a) units in the generating system (supply side): capability, and forced outage rate, and

(b) the pattern of demand (demand side). (For simplicity, we will summarize the pattern in the simulation with one parameter, the daily peak load.)

In summary, our simulation model consists of Equations 4-3a, 4-3b, 4-4a, 4-4b, 4-5a, 4-9, and 4-10. The data simulation framework is built on this system of seven equations. We discuss the details of the simulation procedure and data base in the following section.

4.1.2 Data and Simulation Procedures

The rating periods used to define peak and off-peak in this simulation test are illustrated below:

12 midnight off-peak
8 a.m.
peak (10 hrs.)
6 p.m.
12 midnight off-peak

Thus, the reference load pattern is very simple, as shown in Figure 4-2. The dotted lines represent the net result of two factors: price structure and random demand shocks.

To obtain peak and off-peak load patterns, we use a random number generator to provide normally distributed load data for a reference load shape: peak load (with a mean of instantaneous peak load $\overline{x}_p$ = 46.5MW and a standard deviation s_p = 5.5 MW) and off-peak load (mean $\overline{x}_{op}$ = 23.5 MW and a standard deviation s_{op} = 5.5 MW). Thus, each day (for a thirty-day period) has a different load shape. To achieve annualized numbers, the monthly KWH observation was multiplied by twelve. The peak instantaneous KW demand was also used in the regression analysis. Thus, long run capacity adjustments and seasonal variations in generating unit

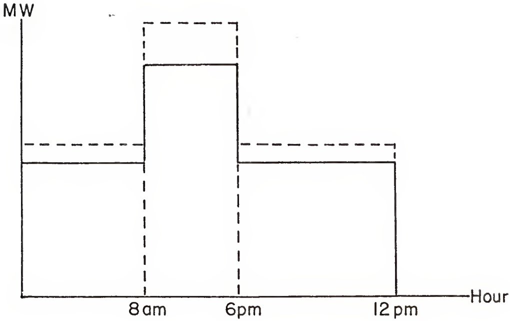


Figure 4-2. Reference Load Patterns and Shifts Due to Prices and Random Shocks

maintenance or load patterns are not being considered here. The same reference load pattern is used for each generation mix. The random loads were created by using the reference load adjusted by a random factor multiplier $\phi = (\varepsilon)0.00005((-1)^{mn})(mn)$,

where

ϕ = the random multiplier determining the size of the shift,

ε = the elasticity adjustment factor,

m = the m^{th} price combination (m = 1 . . . 60), and

n = the n^{th} day (n = 1 . . . 30).

Thus, the reference load is shifted up or down, depending on the day and price combination. The size of the shift (relative to the reference load) depends on the price combination, the associated elasticities, and a purely random factor.

We have developed two major groups of scenarios which vary in price and demand elasticity (own and cross). All relevant parameters of two major groups mentioned above are summarized in Table 4-1. (The derivation of these parameters is fully discussed throughout the rest of this chapter.) Each major group is composed of four subgroups based on different capacity mixes, which are specified in Figure 4-3.

The decision regarding the selection of unit size and numbers of units is based on economic and engineering considerations. The former refers to load patterns and load growth, capacity, and fuel costs. The latter refers to engineering efficiency. (The full treatment of this issue is beyond the scope of this study.) For this simulation, the selection of reference capacity mix (K-mix) is based on the following load considerations. As we generated peak and off-peak demand in the

Table 4-1. Creation of Pseudo Data

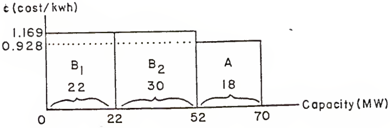
Scenario	1	2	3	4	5	6	7	8
Capacity Mix (Four types, see Figure 4-3 for detail)	K-mix 1	K-mix 1	K-mix 2	K-mix 2	K-mix 3	K-mix 3	K-mix 4	K-mix 4
Production Cost								
(i) Capacity charge (β)								
Peak Unit (¢/KWH)	0.929	0.929	0.929	0.929	0.929	0.929	0.929	0.929
Base Unit (¢/KWH)	1.169	1.169	1.169	1.169	1.169	1.169	1.169	1.169
(ii) Fuel Charge (b)								
Peak Unit (¢/KWH)	3.902	3.902	3.902	3.902	3.902	3.902	3.902	3.902
Base Unit (¢/KWH)	1.887	1.887	1.887	1.887	1.887	1.887	1.887	1.887
Price Elasticities								
(i) Own Elasticities								
(a) Peak	0.492	0.241	0.492	0.241	0.492	0.241	0.492	0.241
(b) Off-peak	0.487	0.315	0.487	0.315	0.487	0.315	0.487	0.315
(ii) Cross Elasticities								
(a) Peak	0.01	0.02	0.01	0.02	0.01	0.02	0.01	0.02
(b) Off-peak	0.06	0.05	0.06	0.05	0.06	0.05	0.06	0.05
Price Combinations (60 combinations, 3 subgroups)								

(i) 1.5¢ price difference for the first 20 combinations
(ii) 2¢ price difference for the second 20 combinations
(iii) 4¢ price difference for the last 20 combinations

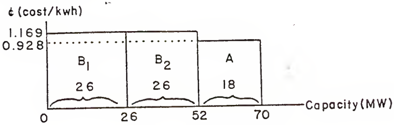
Note: -For all 8 scenarios, see Appendix A, column 1, for the complete price list.

-There are 60 price combinations and 30 daily loads (peak and off-peak). Therefore, we have 3600 data points (i.e., 2 x 60 x 30) for each scenario. For the empirical tests, these are summarized into 120 observations per capacity mix.

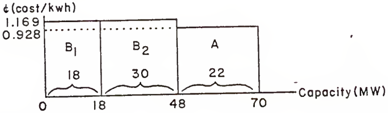
(1) Reference Mix



(2) Equal Size Base Units



(3) Relatively More Peaking Capacity



(4) High Total Capacity

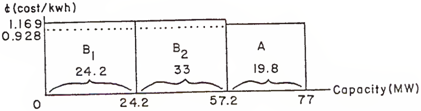


Figure 4-3. Four Generating Mixes (Minimal Capacity Variance)

earlier paragraphs, we have

(i) $\bar{x}_p = 46.5$ MW $\qquad s_p = 5.5$ MW;

therefore

$p(\bar{x}_p \leq \bar{x}_p + s_p = 46.5 \text{ MW} + 5.5 \text{ MW} = 52\text{MW}) \doteq 84\%$.

We make total base capacity equal to the mean plus one standard deviation (i.e., $B_1 + B_2 = 52$ MW). We assume that Unit $B_1 = 22$ MW, Unit $B_2 = 30$ MW.

(ii) $\bar{x}_{op} = 23.5$ MW $\qquad s_{op} = 5.5$ MW,

therefore

$p(\bar{x}_{op} \leq \bar{x}_{op} + 3s_{op} \doteq 23.5 \text{ MW} + 3(5.5 \text{ MW}) = 40 \text{ MW}) = 99\%$.

We have to make Unit A = 18 MW in order to satisfy off-peak demand if either B_1 or B_2 is out because of forced outage or scheduled maintenance. The following four types of capacity variations (see Figure 4-3) were created to explore the cost implications of alternative capacity mixes.

1. Reference k-mix: total capacity = 70 MW,
   Base Units: Unit B_1 (22 MW), Unit B_2 (30 MW), and
   Peak Unit: Unit A(18 MW);

2. Equal size Base Units: total capacity = 70 MW,
   Base Units: Unit B_1 (26 MW), Unit B_2 (26 MW), and
   Peak Unit: Unit A (18 MW);

3. Mix of Peak Unit and Off-Peak Unit: total capacity = 70MW,
   Base Units: Unit B_1 (18 MW), Unit B_2 (30 MW), and
   Peak Unit: Unit A (22 MW) (i.e., relatively more peaking capacity);

4. Change in Total Capacity: total capacity = 77 MW (i.e., 10 percent capacity increase for all units),
   Base Units: Unit B_1 (24.2 MW), Unit B_2 (33 MW), and
   Peak Unit: Unit A (19.8 MW).

The base price (uniform price) is assumed to be 6¢ per KWH, which happens to be the average electricity price in the State of Florida in

1981. In the simulation, 60 different price combinations were used for each generation mix. Each price combination represents one set of peak and off-peak price. The price differences between peak and off-peak price are specified as follows:

1. For the first 20 price combinations the peak and off-peak price differences are 1.5¢,
2. For the second 20 price combinations the peak and off-peak price differences are 2¢, and
3. For the last 20 price combinations the peak and off-peak price differences are 4¢.

The set of time-of-day price elasticities were selected from a load study by Cargill and Meyer (1971). The data base of Cargill's study consists of monthly observations on the twenty-four hour load curve in one-hour intervals for two regions during the four-year period from January 1965 through December 1968. The first region is a large midwest industrial area and the second is a west coast agricultural region. Their estimated price elasticities for each hour are presented in Table 4-2.

Since our peak hours are defined from 8 a.m. to 6 p.m., the peak and off-peak elasticities are the average hourly elasticities in two periods (peak and off-peak). These two elasticities are taken to be as follows:

	Region 1	Region 2
Peak	0.492	0.241
Off-peak	0.487	0.315

Table 4-2. Time of Day Price Elasticities

Hour	Region 1	Region 2
1 a.m.	-0.50	-0.49
2	-0.50	-0.52
3	-0.51	-0.42
4	-0.51	-0.48
5	-0.50	-0.48
6	-0.49	-0.29
7	-0.58	-0.27
8	-0.56	-0.23
9	-0.56	-0.27
10	-0.57	-0.35
11	-0.53	-0.34
12 noon	-0.48	-0.26
1 p.m.	-0.43	-0.19
2	-0.47	-0.20
3	-0.44	-0.20
4	-0.43	-0.18
5	-0.46	-0.09
6	-0.44	-0.18
7	-0.45	-0.06
8	-0.57	-0.15
9	-0.55	-0.18
10	-0.45	-0.23
11	-0.39	-0.30
12 midnight	-0.38	-0.35

Data Source: Cargill and Meyer, (1971).

Cross-elasticities used in these scenarios are presented as follows:

	Region 1	Region 2
Peak	0.01	0.02
Off-peak	0.06	0.05

4.1.3a Welfare Calculations

Now we turn to the discussion of estimation of consumer surplus. In Equation 4-9, net change in consumer surplus caused by price change can be represented by the area PP''GE in Figure 4-4, which can be approximated by the following equation:

$$\begin{aligned}\Delta CS &= (P - P'')Q + \tfrac{1}{2}((P - P'')(Q'' - Q))\\ &= (P - P'')(Q + \tfrac{1}{2}(Q'' - Q))\\ &= \tfrac{1}{2}(P - P'')(Q + Q''), \qquad (4\text{-}11)\end{aligned}$$

where

ΔCS = net change in consumer surplus,

P = price before price change,

Q = quantity before price change,

P'' = price after price change, and

Q'' = quantity after price change.

The above estimation is based upon the assumption that the demand function is linear and independent.

4.1.3b Capacity Cost Calculations

The selection of generator unit size (i.e., capacity level) and number of generation units are determined by historical load patterns. The simulation results reported here do not reflect the cost of optimal

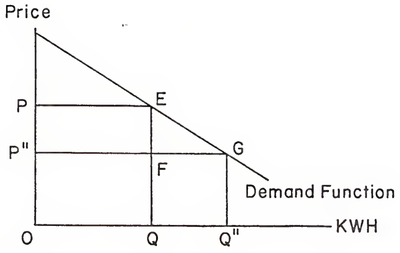


Figure 4-4. Net Change in Consumer Surplus

generating mixes for the ex post load pattern. This characteristic is not a severe limitation, since the generating mixes of most electric utilities were non-optimal in the late 1970s, given the input prices after the OPEC-induced petroleum price rises. The stochastic demands are still met with minimum operating costs. So the costs and outputs observed are not unlike the data actually reported by electric utilities during similar time periods.

Since we are dealing with an extremely simple production technology, we further assume that the generator capacity is divisible. This simplifying assumption does not violate the essential feature of a diverse technology production environment. Also, note that this utility model assumes a closed system, so it does not consider electricity imports or exports. That is, power pooling issues do not arise.

In this simulation, we assume there are three generating units. Unit B_1 and Unit B_2 are coal-fired base units. Unit A is the oil-fired peaking unit. The capacity cost can be defined in terms of the concepts developed in the previous chapter.

The annual capacity cost if unit i, denoted by β_i^*, is defined as follows:

$$\beta_i^* = F_i cc_i K_i, \tag{4-12}$$

where

F_i = fixed charge rate,

cc_i = generator capacity acquisition cost (\$/MW),

K_i = capacity in MW, and

β^* = total annualized capacity cost.

We use the above definition to calculate an annual capacity cost. Further, if Equation 4-12 were divided by the expected value of the annual energy produced by unit i, denoted by $\varepsilon(E_i)$, then the capacity cost might be expressed in Mils/KWH or \$/MWH.

We have

$$\frac{\beta_i^*}{\varepsilon(E_i)} = \frac{F_i cc_i k_i}{\varepsilon(E_i)} = \frac{F_i cc_i k_i}{3{,}650(CF_i k_i)} ,$$ (since we have 10 hours peak in simulation, so $\varepsilon(E_i) \simeq 3{,}650(CF_i k_i)$),

$$\beta_i = \frac{F_i cc_i}{3{,}650(CF_i)} , \tag{4-13}$$

where

CF_i = capacity factor.

The capacity factor is the ratio of the average load to the total plant capacity. Given the simultaneity problem linking KWH consumption to this number we will assume that CF = 0.8 for all base units, CF = 0.2 for the peaking unit, and the generator acquisition costs (unit capacity costs) are assumed as follows:

UC (30 MW) = \$190/KW,

UC (18 MW) = \$195/KW, and

UC (22 MW) = \$ 65/KW.

Then, we use Equation 4-13 to calculate capacity cost (β_i) as follows:*

(i) Base Units:

$$\beta_{30MW} = \frac{F_i cc_i}{3{,}650(CF_i)} = \frac{0.179(190)10^3}{3{,}650(0.8)} = 11.49 \text{ Mills/KWH} = 1.149¢/\text{KWH},$$

---

*We make the following assumptions regarding the generator units: 1) straight-line depreciation, 2) life of generator is assumed to be 10 years, and 3) zero net salvage value. Also, we assume the depreciation rate = 10%, the tax rate = 5.7%, other local and state taxes = 1.6%, and the insurance rate = 0.6%. Thus, the sum of the above percentages is 17.9 percent, and the fixed charge rate (FCR) is 0.179 for all units.

where $F_i = 0.179$;

$$\beta_{18MW} = \frac{0.179(195)10^3}{3,650(0.8)} = 1.188¢/KWH.$$

Thus, a base unit capacity cost of 1.169¢/KWH has been used in this simulation test.

(ii) Peaking Unit:

$$\beta_{22MW} = \frac{0.179(65)10^3}{3,650(0.2)} = 0.9288¢/KWH.$$

Fuel prices are major factors in determining the production cost. According to the 1980 fuel price level, it costs 1.877 ¢/KWH for a coal unit (10,485 BTUs x \$1.8 per million BTU = 1.887 ¢/KWH), and 3.902 ¢/KWH for an oil unit (10,485 BTUs x \$3.722 per million BTU = 3.902 ¢/KWH). According to composite averages (all fuel consumed for the State of Florida in the year 1980), BTU per net KWH is equal to 10,485.*

Three reliability indices are simultaneously used in this simulation test: Expected demand not served ε(DNS), loss of load probability (LOLP), and reserve margin (RM). Since load may be lost due to many causes, and only a shortage of generating capacity is considered in the LOLP method. This index is measured in expected days of capacity shortage per year, and is often referred to as a system's risk index. The risk index (LOLP), is affected by the installed capability and peak load just as is the percent reserve index; however, the LOLP is also sensitive to the various sizes and outage rates of the installed generator, the load shape, and maintenance scheduling. For this simulation test, the following table provides the necessary information to calculate loss of load probability.

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*The British Thermal Unit (BTU) is the standard unit for measuring the quantity of heat energy, such as the heat content of fuel. It is defined as the amount of heat energy necessary to raise the temperature of one pound of water one degree Farenheit.

Table 4-3 contains the forced outage parameters used in this simulation. The largest unit, B_2, is assumed to have the highest forced outage rate where the definition of forced outage rate is

$$\text{Forced outage rate} = \frac{\text{forced unavailable hours}}{\text{service hours + forced unavailable hours}} \tag{4-14}$$

In a more realistic modeling exercise, unit forced outage rates would be taken from the referenced EEI publication or alternatively from a utility company's historical operating records on the unit in question. We assume independence of unit outage, so a cumulative outage probability table can be calculated. (See Table 4-4 for the appropriate figures.)

To calculate reliability indices, the generating system is represented by a capacity outage table, which requires enumerating all possible combinations of the units in or out of service and the associated probability of occurrence for each combination. Table 4-4 contains an outage probability table which shows both exact outage (the particular outage case) and cumulative outage probability.

As to the calculation of expected demand not served, $\varepsilon(\text{DNS})$ can be defined as follows:

$$\begin{aligned} \varepsilon(\text{DNS}) &= E(D - S) \\ &= E(x) \\ &= \sum_{i=1}^{n} x_i \, f(x_i), \end{aligned} \tag{4-15}$$

Table 4-3. Forced Outages for Units in Generating System

Unit	Capability (MW)	Forced Outage Rate	Inage Rate
B_1	22	0.01	0.99
A	18	0.02	0.98
B_2	30	0.03	0.97

Table 4-4. Exact Outage and Cumulative Outage Probability Table

Case	On Outage (X MW)	Probability	In Service (MW)	Probability of X or Greater on Outage
1	None (0)	0.99 x 0.98 x 0.97 = 0.941094	70	1.000000
2	A (18)	0.99 x 0.02 x 0.97 = 0.019206	52	0.058906
3	B_1 (22)	0.01 x 0.02 x 0.97 = 0.009506	48	0.039700
4	B_2 (30)	0.99 x 0.98 x 0.03 = 0.029106	40	0.030194
5	A, B_1 (40)	0.01 x 0.02 x 0.97 = 0.000194	30	0.001088
6	A, B_2 (48)	0.99 x 0.02 x 0.03 = 0.000594	22	0.000894
7	B_1, B_2 (52)	0.01 x 0.98 x 0.03 = 0.000294	18	0.000300
8	A, B_1, B_2 (70)	0.01 x 0.02 x 0.03 = 0.000006	0	0.000006

Note: Unit B_1 capacity = 22 MW (Base)
Unit A capacity = 18 MW (Peak)
Unit B_2 capacity = 30 MW (Base)

where

D = peak load, and

S = supply of electricity.

Both D and S are random variables, and if we let $x = D - S$, x becomes a discrete random variable. As an illustration, consider the following example.

Let the peak load on the 7th day be 21 MW. What is the expected demand not served? An outage of more than 49 MW (i.e., total available capacity (70 MW) minus peak load (21 MW) equals 49 MW) will cause a loss of load. In other words, only Cases 7 and 8 in Table 4-4 will cause a loss of load. Therefore, if Case 7 occurs, then DNS = 21 - 18 = 3 MW, where

DNS = peak load - capacity in service.

Also,

$f(x_1)$ = Prob (Case 7) = 0.000294.

If Case 8 occurs, then

DNS = 21 - 0 = 21 MW;

$f(x_2)$ = Prob (Case 8) = 0.000006.

By using Equation 4-15 we obtain

$$E(X) = \sum_{i=1}^{2} x_i\ f(x_i) = 3 \times 0.000294 + 21 \times 0.000006 = 1.008 \text{ KW}.$$

Accordingly, the expected demand not served for the 7th day is 1.008 KW with a probability of 0.0003. Since both ε(DNS) and LOLP are created from the same set of data, we are now able to understand that one side of the two-way mirror is LOLP; the other side is ε(DNS), measured in KW per time period.

The summary of all the relevant parameters used in this simulation test is found in Table 4-5. Relevant parameters for two groups of

Table 4-5. Parameter List of Simulation Test

	Group 1 (Scenario 1, 3 and 5, 7)	Group 2 (Scenario 2, 4 and 6, 8)
Uniform Price	6¢/KWH	6¢/KWH
Price Elasticity		
Peak	0.492	0.241
Off-peak	0.487	0.315
Cross Price Elasticity		
Peak	0.01	0.02
Off-peak	0.06	0.05
Production Cost		
Capacity Charge (β)		
Base Unit		
Unit B_1	1.169¢/KWH	1.169¢/KWH
Unit B_2	1.169¢/KWH	1.169¢/KWH
Peaking Unit		
Unit A	0.9288¢/KWH	0.9288¢/KWH
Fuel Cost (b)		
Coal (base)	1.887¢/KWH	1.887¢/KWH
Oil (peak)	3.902¢/KWH	3.902¢/KWH

scenarios were listed separately. These parameters are uniform price, price elasticity, price cross elasticity, capacity charge, and fuel cost.

Up to this point, we have specified and described all the required simulation procedures and data base. All the simulation results and further econometric analysis are presented in the next chapter.

CHAPTER V
EMPIRICAL ESTIMATES OF THE ELECTRICITY COST OF RELIABILITY AND PRODUCTION

We now review the potential significance of the simulation results by performing some fundamental econometric analyses and making numerical comparison. We are mainly concerned with the estimation of cost of reliability by using pseudo data. We are also interested in some implications of the simulation for non-cost dimensions of performance. For example, we can obtain a set of welfare-maximized TOU prices subject to reaching a given level of reliability constraint.

5.1 Structure of the Model

The first major task in this section is to conduct an econometric analysis based on results from the simulation test. That is, we need to estimate the cost of reliability equations to assist us in power planning and investment decisions. By examining Table 4-4, we see that there are eight possible outage combinations. Each of the situations involves different sets of generating unit status (i.e., up or down). Therefore, each of the cases has a different combination of production costs and reliability for a given load pattern.

5.1.1 Determinants of Reliability

Before going into the estimation model, we will give a brief discussion of determinants of reliability. Most power outages occur during the peak hour, so the instantaneous peak KW demand will affect the reliability of an entire power system. The reliability is negatively related to peak electricity demand which is also negatively related to peak price. Thus, reliability is positively related to peak price.

Load factor is defined as the ratio of the average load in KW supplied during a designated period to the peak or maximum load in KW occurring in that period. Accordingly, the higher the load factor, the lower the system reliability will tend to be, for the same generation mix.

5.1.2 The Model

The functional relationship of the model is formally described as follows:

$$C = f(X, R, \varepsilon), \text{ and} \tag{5-1a}$$

$$R = g(p, L, \mu), \tag{5-2a}$$

where C denotes the dependent variable, total cost, and

X = total electricity consumption,

R = reliability,

p = price of electricity,

L = peak load, and

ε, μ = disturbance terms.

Regressor R in the above system of equations is endogenous, stochastic, and correlated with the regression disturbance. In this case, the ordinary least squares estimators of the regression coefficients are inconsistent.* There are several methods leading to consistent estimation. For simultaneous equation systems (including the recursive system), the best known common method is that of two-stage least squares. In considering Equation 5-2a, L and P are closely correlated** because $L_i = 1(P_i)$; we need to drop P so that Equation 5-2a is modified for estimation purposes as follows:

$$R_i = \gamma_0 + \gamma_1 \cdot L_{ijk} + \mu_i. \tag{5-2b}$$

We can also rewrite Equation 5-1a in this form:

$$C_i = \beta_0 + \beta_1 \cdot X_{ijk} + \beta_2 \cdot R_{ijk} + \varepsilon_i \tag{5-1b}$$

where

i = k-mix
= 1 . . . 4,
j = elasticity combination
= 1, 2, and
k = price combination
= 1, 60.

On a priori grounds, we may hypothesize the sign for some of the variables. In the cost equation, we expect positive marginal production cost, so the sign of the X coefficient (total electricity consumption), β_1, is positive, and the sign of the R coefficient (reliability), β_2, is expected to be positive, since other things being equal, higher reliability will cause higher cost. Therefore, the sign of R is as follows:

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*See Kmenta, "Elements of Econometrics," Chapter 13. In Section 13-1, he emphasized that the ordinary least squares method of estimation applied to the structural equations of a simultaneous equation system, and, in general, leads to inconsistent estimates. A high degree of multicollinearity exists whenever one explanatory variable is highly correlated with another explanatory variable or with a linear combination of other explanatory variables. Multicollinearity implies that the higher the degree of multicollinearity, the larger the variances of estimators and the co-variances between estimators.

**The multicollinearity problem is not precisely eliminated by suppressing p, rather, γ-1 will be a composite coefficient showing the effects of both p and L.

if R is LOLP, $\beta_2 < 0$,
if R is ε(DNS), $\beta_2 < 0$, and
if R is RM, $\beta_2 > 0$.

In the reliability equation, the sign of peak load is hypothesized as follows:

if R is LOLP, $\gamma_1 > 0$,
if R is ε(DNS), $\gamma_1 > 0$, and
if R is RM, $\gamma_1 < 0$.

Equations 5-1b and 5-2b belong to a system of linear equations. We can test whether a nonlinear model will yield a better fit. Such a system of non-linear models is hypothesized as follows:

$$C_i = \beta_0 \cdot X_{ijk}^{\beta_1} \cdot R_{ijk}^{\beta_2} \cdot e^{\varepsilon_i} \text{ , and} \tag{5-3}$$

$$R_i = \gamma_0 \cdot L_{ijk}^{\gamma_1} \cdot e^{\mu_i} \text{ .} \tag{5-4}$$

We can also transform the above equations into a linear model in logarithmic form by taking logarithms (to base e) of both sides of Equations 5-3 and 5-4:

$$\ln C_i = \ln \beta_0 + \beta_1 \cdot \ln X_{ijk} + \beta_2 \cdot \ln R_{ijk} + \varepsilon_i \text{ , and} \tag{5-5}$$

$$\ln R_i = \ln \gamma_0 + \gamma_1 \cdot \ln L_{ijk} + \mu_i \text{ ,} \tag{5-6}$$

which can be written as

$$C_i^* = \beta_0^* + \beta_1 \cdot X_{ijk}^* + \beta_2 \cdot R_{ijk}^* + \varepsilon_i \text{ , and} \tag{5-7}$$

$$R_i^* = \gamma_0^* + \gamma_1 \cdot L_{ijk}^* + \mu_i \text{ ,} \tag{5-8}$$

where

$C^*_i = \ln C_i$,

$X^*_{ijk} = \ln X_{ijk}$,

$R^*_{ijk} = \ln R_{ijk}$,

$L^*_{ijk} = \ln L_{ijk}$,

$\beta^*_0 = \ln \beta_0$, and

$\gamma^*_0 = \ln \gamma_0$.

Here, the starred symbol represents the logarithms of the unstarred counterparts.

5.2 Econometric Results

We apply the two-stage least square (2SLS) estimation method to both the linear model (i.e., Equations 5-1b and 5-2b) and the logarithmic model (i.e., Equations 5-7 and 5-8). Since three reliability indices have been used in this study, we will estimate the equation for each index, yielding six sets of estimations for each capacity mix (since there are two models, linear and logarithmic, and three reliability indices, LOLP, ε(DNS), and RM).

5.2.1 Hypothesis Testing

For the evaluation of econometric results, we need to discuss methods of testing the hypotheses. The null hypothesis is H_0: $\beta = 0$. We wish to test H_0 at a one percent level of significance. Since we have 120 observations for each K-mix, the appropriate value of the t-statistic for a two-tail test is the value corresponding to $t_{117,\ 0.005}$, for the cost equation, and $t_{118,\ 0.005}$ for the reliability equation.

The acceptance region for our test is

$$-2.576 \leq \frac{\hat{\beta}}{S_{\hat{\beta}_i}} \leq 2.576 . \tag{5-9}$$

Also, the tabulated values of $F_{k-1,\ n-k}$ (i.e., $F_{2,\ 117}$ and $F_{1,118}$) at the 1 percent level of significance are 4.81 and 6.87 respectively.

Based on these results, we make the following conclusions regarding R^2s, t-values, and F-values:

(1) These t-values of all estimated coefficients of both linear and logarithmic models are out of the acceptance region as indicated by Equation 5-9. Thus, all estimated coefficients are statistically significant and the null hypotheses would be rejected.

(2) The F values are also out of acceptance region. That is, the evidence strongly suggests that all explanatory variables significantly contribute to the explanation of variation in cost.

(3) All R^2s are high enough to claim a good fit; however, there is not much R^2 variation among all cost equations, that is, they are all over 99 percent, suggesting multicollinearity.

(4) The logarithmic model has a built-in elasticity measure. For example, in Equation 5-7, β_1 measures production elasticity of cost and β_2 measures reliability elasticity of cost. We will further elaborate such measures in the following sections.

5.2.2 Interpretation of Coefficients on Reliability and Cost

We now turn to the implications of estimated models. The reliability elasticity of cost is defined as

$$E_{RC} = \frac{\partial(\ln C)}{\partial(\ln R)} .$$

Similarly, the electricity production cost elasticity is defined as

$$E_{XC} = \frac{\partial(\ln C)}{\partial(\ln X)} .$$

We can derive the above elasticities from a log model. Table 5-1 presents all three reliability elasticities of cost. The meanings of the numbers in Table 5-1 are very straightforward. For instance, -0.0106 means that a 1 percent decrease in LOLP (i.e., reliability increases) will result in a 0.0106 percent cost increase. (It should be noted that the elasticities in Table 5-1 are inelastic.)

In the long run, an improvement of reliability can be obtained by investing in additional generating units. In theory, $\frac{\partial C}{\partial R} > 0$, (Both cost and reliability move in the same direction).

In the short run, any generator outage will reduce service reliability and total electricity production. Since the capacity cost of an out-of-service unit is included in the calculation of total cost, the total cost is reduced due to less fuel usage. Thus, $\frac{\partial C}{\partial R} > 0$, should still hold true in the short run. In Table 5-1, the signs of the coefficients under the RM column are all negative. However, in theory, they should be positive. This discrepancy suggests that if the reliability index is reserve margin, then the log model should not be utilized. We can also derive the following findings by comparing the coefficients in Table 5-1:

(i) For all four types of k-mix, costs are less sensitive to the LOLP reliability index than to ε(DNS), since the absolute value at each LOLP coefficient is smaller.

(ii) To compare k-mix Type 1 (reference k-mix) and k-mix Type 2 (two equal size base units), the latter has smaller elasticity. That is, the greater the generator size variation, the greater the cost sensitivity.

(iii) To compare k-mix Type 1 (reference mix) and k-mix Type 3 (larger peaking unit), Type 3 k-mix has larger elasticities, which suggests that having a larger peaking unit in the capacity mix tends to cost more due to a given reliability change.

(iv) To compare k-mix Type 1 (reference mix) and k-mix Type 4 (10 percent capacity increase for all units), we see that the

Table 5-1. Reliability Elasticity of Cost*

K-mix Type		LOLP	ε(DNS)	RM
1	Reference mix	-0.0106	-0.0150	-0.19
2	Two equal-size base units	-0.0077	-0.0086	-0.19
3	Larger peaking unit	-0.0140	-0.0170	-0.29
4	Ten percent increase for all units	-0.0340	-0.0570	-0.10

*Note that a drop in LOLP or ε(DNS) implies an increase in reliability; therefore, a negative sign means that costs rise as reliability increases.

reliability elasticity of cost is getting larger as the total capacity of generators is increasing.

Table 5-2 summarizes the marginal cost of production (holding reliability constant), which are derived from our linear model. We can see that the standard errors in the ε(DNS) column are the smallest among all three reliability indices, which suggests that perhaps the ε(DNS) model gives the best estimate of the marginal cost of electricity production. By comparing k-mix Type 1 with k-mix Type 4, we also see that marginal costs are increasing as the sizes of generators are increasing for both LOLP and ε(DNS) models.

Table 5-3 summarizes the sensitivity coefficients of reliability to peak demand, that is, $\frac{\partial(\ln R)}{\partial(\ln L)}$. These coefficients provide insight into reliability change with respect to peak demand. Looking at the ratio, we can see that the ε(DNS) model has a substantially lower standard error for all types of k-mixes indicating that the ε(DNS) model may provide the best estimate of reliability change with respect to peak demand change. Also, by comparing k-mix Type 1 with k-mix Type 4, we once again see that k-mix Type 4 has larger coefficients for both LOLP and ε(DNS) models. This means that reliability of k-mix with larger units is more sensitive to peak demand change.

Another interesting parameter,

$$\frac{\partial(\ln C)}{\partial(\ln L)} = \frac{\partial(\ln C)}{\partial(\ln R)} \cdot \frac{\partial(\ln R)}{\partial(\ln L)},$$

can indicate the sensitivity of cost to peak demand. The term has been described in Table 5-1, and the term $\frac{\partial(\ln R)}{\partial(\ln L)}$ has been summarized in Table 5-3. Thus, we can easily derive $\frac{\partial(\ln C)}{\partial(\ln L)}$ by the multiplication of these previous coefficients. Table 5-4 summarizes these sensitivity parameters.

Table 5-2. Marginal Costs of Production (Linear Model)

K-mix Type	LOLP	ε(DNS)	RM
1	1.74 (s = 0.0210)	1.47 (s = 0.0110)	1.89 (s = 0.060)
2	1.56 (s = 0.0170)	1.53 (s = 0.0040)	1.86 (s = 0.058)
3	1.87 (s = 0.0360)	1.45 (s = 0.0085)	2.02 (s = 0.099)
4	1.83 (s = 0.0057)	1.84 (s = 0.0030)	1.64 (s = 0.010)

Note: s = standard error.

Table 5-3. Reliability Sensitivity Coefficients

K-mix Type	LOLP	ε(DNS)	s_1/s_2
1	5.99 (s_1 = 0.157)	7.99 (s_2 = 0.057)	2.75
2	9.09 (s_1 = 0.190)	9.13 (s_2 = 0.040)	4.75
3	6.10 (s_1 = 0.160)	8.02 (s_2 = 0.056)	2.86
4	8.60 (s_1 = 0.180)	9.51 (s_2 = 0.087)	2.06

Table 5-4. Cost Sensitivity to Peak Demand

K-mix Type	LOLP	ε(DNS)
1	-0.0635	-0.1199
2	-0.0700	-0.0785
3	-0.0854	-0.1360
4	-0.2924	-0.5420

Looking at k-mix Type 4 and k-mix Type 1, we find that cost sensitivity goes up 5 times as the capacity of generator units is increased only 10 percent. Thus, it appears that the capacity mix is very cost sensitive to peak demand.

5.2.3 Interpretation of Cost Equations: Comparisons between Models with Reliability Variables and without Reliability Variables

By examining Table 5-5, the logarithmic model, we found that the R^2 of models with reliability variables are slightly higher than the R^2 of the model without reliability variables. Thus, the explanatory power of the model is improved by including reliability variables into the cost model. Note that the most meaningful interpretation of the model with reliability variables is to assess the impact of reliability on cost, even though the improvement of R^2 is small. The statistical hypothesis-testing showed that all those estimated coefficients are statistically significant. Looking at the coefficients of total electricity consumption in Table 5-5, (i.e., $\frac{\partial(\ln C)}{\partial(\ln X)}$), we found those models with either LOLP or ε(DNS) have higher coefficients. However, for K-mix Type 4, such coefficients are only slightly higher.

Looking at Table 5-6, the linear model, all R^2 are above 99 percent. The marginal cost of electricity production for the model without the reliability variable also moves higher as each generator unit is increased by 10 percent, that is, K-mix Type 4. Similar to the log model, the inclusion of reliability in the model does not improve R^2 substantially. However, it does enable us to assess the impact of reliability on cost. By pooling the data from all four mixes (reported

Table 5-5. Comparisons of Log Models with and without the Reliability Variable

	Model without Reliability Variable	Model with LOLP Variable	Model with ε(DNS) Variable
K-mix Type 1			
1. Total electricity consumption	0.479	0.5500	0.6060
2. Reliability index	-	-0.0106	-0.0150
3. Constant term	7.680	6.8800	6.1900
4. R^2	99.67%	99.89%	99.82%
K-mix Type 2			
1. Total electricity consumption	0.482	0.5600	0.5600
2. Reliability index	-	-0.0077	-0.0086
3. Constant term	7.640	6.7500	6.4600
4. R^2	99.69%	99.85%	99.73%
K-mix Type 3			
1. Total electricity consumption	0.535	0.6200	0.6800
2. Reliability index	-	-0.0140	-0.0170
3. Constant term	6.940	5.9000	5.1900
4. R^2	99.49%	99.82%	99.65%
K-mix Type 4			
1. Total electricity consumption	0.450	0.4800	0.4600
2. Reliability index	-	-0.0340	-0.0570
3. Constant term	8.070	7.7100	8.7800
4. R^2	99.55%	99.97%	99.97%

Table 5-6. Comparisons of Linear Models with and without the Reliability Variable

	Model without Reliability Variable	Model with LOLP Variable	Model with ε(DNS) Variable
K-mix Type 1			
1. Total electricity consumption	1.66	1.74	1.47
2. Reliability index	-	-715.60	173.20
3. Constant term	420,934	404,700	460,187
4. R^2	99.89%	99.91%	99.97%
K-mix Type 2			
1. Total electricity consumption	1.67	1.56	1.53
2. Reliability index	-	788.48	171.70
3. Constant term	418,539	440,745	448,914
4. R^2	99.90%	99.93%	99.99%
K-mix Type 3			
1. Total electricity consumption	1.79	1.87	1.45
2. Reliability index	-	-580.70	293.86
3. Constant term	360,662	346,151	428,984
4. R^2	99.77%	99.78%	99.99%
K-mix Type 4			
1. Total electricity consumption	1.82	1.83	1.84
2. Reliability index	-	-184.70	-21.40
3. Constant term	504,612	500,796	500,674
4. R^2	99.99%	99.99%	99.99%

in the next section), we find that the reliability variable significantly improves the power of the model.

5.3 Comparison of Small Variation k-Mix and Large Variation k-Mix

The examination of specific capital mixes involved substantial multicollinearity. Here, we analyze the results when the data are pooled. In addition, in order to explore the significance of k-mix variation on the estimation of the cost equation, we define another set of four capacity mixes as a large variation k-mix group. This new group contrasts with the small variation k-mix group described in Figure 4-3, whose model tests were reported previously. The four mixes include:

1. Reference mix (Total capacity = 70 MW)
   Unit B_1 = 22 MW, Unit B_2 = 30 MW, Unit A = 18 MW
2. Low capacity mix (Total capacity = 60 MW)
   Unit B_1 = 21 MW, Unit B_2 = 25 MW, Unit A = 14 MW
3. Lowest capacity mix (Total capacity = 50 MW)
   Unit B_1 = 20 MW, Unit B_2 = 20 MW, Unit A = 10 MW
4. High capacity mix (Total capacity = 80 MW)
   Unit B_1 = 25 MW, Unit B_2 = 35 MW, Unit A = 20 MW

Given the problems with interpreting results for specific capital mixes, we proceed directly to the capital mix groupings. The results of model test are reported in Table 5-7. First, consider models with and without the reliability variable. The addition of LOLP or ε(DNS) enhance the explanatory power. The reported R^2 are substantially increased by including reliability in the model. This result suggests that parameter cost equations reported in the empirical literature could involve biased estimates.

Comparing the small variation group with the large variation group, we find the estimated intercepts in the small variation group are

Table 5-7. Comparisons of Parameter Estimates with and without Reliability Variables

	Model without Reliability Variable	Model with LOLP Variable	Model with ε(DNS) Variable
A. Log Model			
(i) Small variation in K-mix			
1. Total electricity consumption	0.49	1.58	1.96
2. Reliability index	-	- 0.14	- 0.16
3. Constant term	7.59	-57	-10
4. R^2	25.11%	63.78%	64.16%
(ii) Large variation in K-mix			
1. Total electricity consumption	0.55	0.95	1.04
2. Reliability index	-	- 0.05	- 0.06
3. Constant term	6.79	1.92	0.89
4. R^2	29.86%	88.78%	95.87%
B. Linear Model			
(i) Small variation in K-mix			
1. Total electricity consumption	1.74	5.95	4.80
2. Reliability index	-	- 34,589	-3,078.3
3. Constant term	426,037	-399,441	-208,913
4. R^2	23.44%	45.32%	49.51%
(ii) Large variation in K-mix			
1. Total electricity consumption	1.84	2.46	2.65
2. Reliability index	-	-1,446.74	-278.50
3. Constant term	362,213	237,823	195,353
4. R^2	28.82%	57.30%	61.14%

negative when reliability is included as an explanatory variable. These negative intercepts are unreasonable from the standpoint of economic theory. Thus, it may be inappropriate to pool those k-mixes with small variations into a single group. We need to individually estimate each k-mix, as was reported in the previous sections of this chapter. As for the large variation group, the intercept coefficients are statistically significant and of the correct sign.

Turning to the log model versus the linear model comparison, we note that all R^2 of the log models are substantially higher than those R^2 of the linear models. Thus, the log model has greater explanatory power, perhaps because, as Brown and Johnson (1969) note, uncertainty in demand can change a constant cost technology into one with scale economies.

Table 5-8 presents the reliability elasticities of cost estimated from the log model. The three estimated coefficients do have the correct signs. For the large variation in capacity mix, the R^2 of the model with ε(DNS) as the index is highest. As to the reliability elasticity of cost, cost is only slightly more sensitive to the ε(DNS) reliability index than to LOLP. Planners need to integrate into their analysis the benefits associated with small reliability improvements. The results reported here suggest that LOLP and ε(DNS) are highly correlated for the particular cost and demand structures used here.

5.4 Price Setting with Reliability Constraint

In this concluding section, we will present an interesting result of this simulation test. Suppose a power company is considering whether to adopt time-of-day (TOD) pricing. What is the best price structure

Table 5-8. Reliability Elasticity of Cost (Log Model)

	LOLP	ε(DNS)	RM
Small Variation in Capacity Mix	-0.140	-0.160	1.450
	(t = -22.50)	(t = -22.80)	(t = 60.30)
	R^2 = 63.68%	R^2 = 64.16%	R^2 = 81.30%
Large Variation in Capacity Mix	-0.058	-0.063	0.205
	(t = -56.04)	(t = -87.26)	(t = 39.84)
	R^2 = 88.78%	R^2 = 95.87%	R^2 = 83.80%

for the community subject to reaching a given level of reliability constraint? Recall that the capital mix is assumed to be fixed, so we are considering short-run prices (revenue requirements are met through lump sum fees). Assume the electric utility sets the LOLP reliability constraint goal to be less than 2.5 days per year. By reviewing Table 5-9, we can easily locate the best TOD price as 8.4¢ for the peak and 4.4¢ for the off-peak. This is simply because the benefit is maximized subject to the reliability constraint at this particular price combination. Of course, the setting of optimal reliability constraint involves the estimation of cost and benefit of reliability. The estimation of benefit of reliability is beyond the scope of this study; however, this is an important area for future research.

Table 5-9. Illustrative Simulation Results

PRICE	TOTAL REVENUE	TOTAL COST	NET CHANGE IN PROFIT	NET CHANGE IN CONSUMER SURPLUS	NET BENEFIT	LOLP (DAYS/YR)	EDNS (MW/YR)	RESERVE MARGIN
0.051	1065640.00	896177.60	-177272.60	364797.10	187524.50	12.05	109.38	0.4035
0.052	1086802.00	891235.80	-151168.80	334617.30	183448.50	12.05	103.66	0.4070
0.054	1107455.00	886288.30	-125568.30	304688.30	179119.90	11.57	98.03	0.4146
0.055	1127590.00	881424.00	-100569.00	275010.10	174441.10	11.24	92.57	0.4202
0.056	1147204.00	876587.60	-76118.88	245584.10	169465.20	11.24	87.18	0.4258
0.057	1166300.00	871801.00	-52236.06	216410.60	164174.50	10.87	81.92	0.4314
0.059	1184869.00	867116.00	-29782.06	187489.60	158507.50	10.54	76.81	0.4370
0.060	1202920.00	862525.20	-6340.25	158822.60	152482.40	10.08	71.79	0.4426
0.061	1220452.00	857927.10	15789.81	130409.40	146199.20	9.62	66.99	0.4482
0.062	1237472.00	853323.30	37413.63	102251.30	139665.00	9.27	62.46	0.4533
0.064	1253954.00	848777.30	58441.69	74348.56	132790.20	8.92	58.02	0.4594
0.065	1269910.00	844294.80	78880.19	46701.64	125591.80	8.46	53.77	0.4650
0.066	1285339.00	839802.00	98302.00	19310.35	118112.30	8.11	49.77	0.4705
0.067	1300241.00	835301.00	118204.90	-7823.26	110381.60	7.53	45.83	0.4762
0.069	1314601.00	830789.20	137077.70	-34700.05	102377.60	7.18	42.16	0.4819
0.070	1328426.00	826379.40	155311.50	-61318.17	93993.38	6.95	38.60	0.4874
0.071	1341715.00	822089.20	172890.70	-87677.94	85212.81	6.72	35.15	0.4931
0.072	1354444.00	817997.20	189711.70	-113778.00	75933.69	6.37	31.89	0.4987
0.074	1366632.00	814030.60	205866.30	-139618.90	66247.38	6.02	28.72	0.5043
0.075	1378267.00	810067.10	221464.80	-165199.00	56265.75	5.32	25.79	0.5097
0.055	1103193.00	884120.30	-127662.30	305140.10	177477.70	11.24	85.93	0.4261
0.057	1122468.00	879539.90	-103906.90	276680.50	172873.60	10.77	81.89	0.4314
0.059	1141259.00	875051.10	-80527.13	249452.80	167925.60	10.54	77.00	0.4368
0.060	1159575.00	870655.60	-57815.63	220457.10	162641.50	10.08	72.16	0.4422
0.061	1177414.00	866254.80	-35575.88	192694.50	157118.60	9.85	67.55	0.4475
0.062	1194774.00	861848.10	-13807.13	165165.20	151356.10	9.27	63.17	0.4529
0.063	1211660.00	857472.30	7452.63	137870.10	145322.70	8.92	58.89	0.4583
0.065	1228060.00	853183.20	28141.75	110809.50	138951.30	8.46	54.77	0.4636
0.066	1243972.00	848894.90	48352.06	83982.94	132335.00	8.11	50.89	0.4690
0.067	1259400.00	844578.60	68096.31	57391.95	125478.20	8.11	47.06	0.4744
0.068	1274340.00	840262.40	87342.56	31037.16	118379.60	7.18	43.46	0.4798
0.069	1288783.00	835969.40	106058.50	4918.09	110976.60	7.18	40.02	0.4852
0.071	1302736.00	831802.60	124198.30	-20964.13	103234.10	6.95	36.67	0.4906
0.072	1316187.00	827644.30	141607.60	-46608.38	94999.25	6.37	33.45	0.4959
0.073	1329134.00	823976.80	158422.10	-72015.31	86406.81	6.37	30.39	0.5013
0.074	1341584.00	820192.30	174656.60	-97183.25	77473.44	5.67	27.41	0.5067
0.075	1353521.00	816390.70	190395.20	-122112.80	68282.44	4.74	24.78	0.5121
0.077	1364945.00	812576.40	205633.50	-146803.20	58830.31	4.74	22.43	0.5175
0.078	1375881.00	808754.70	220391.20	-171253.20	49138.00	4.04	20.14	0.5229
0.079	1386311.00	804918.60	234657.30	-195463.30	39194.00	4.04	18.10	0.5283
0.076	1208518.00	844420.10	17362.88	86727.00	104089.80	4.74	22.61	0.5171
0.077	1222802.00	840603.00	35264.00	61466.01	96730.00	4.39	20.39	0.5223
0.078	1236622.00	837171.20	52715.75	36420.52	89136.25	4.04	18.44	0.5274
0.080	1249989.00	833535.60	69718.38	11591.43	81309.75	4.04	16.49	0.5326
0.081	1262911.00	829870.00	86255.94	-13020.53	73265.38	3.46	14.76	0.5378
0.082	1275384.00	826239.10	102409.80	-37415.70	64994.11	3.23	13.12	0.5429
0.083	1287392.00	822579.00	118078.00	-61593.36	56484.64	2.65	11.82	0.5481
0.084	1298943.00	818907.60	133300.30	-85552.63	47747.75	2.07	10.78	0.5533
0.085	1310039.00	815230.10	148073.80	-109292.90	38780.94	2.07	9.77	0.5584
0.086	1320685.00	811548.30	162401.60	-132815.00	29586.63	2.07	8.76	0.5636
0.088	1330880.00	807858.10	176296.80	-156117.60	20169.17	1.72	7.86	0.5688
0.089	1340608.00	804161.00	189712.00	-179200.50	10511.50	1.71	7.03	0.5740
0.090	1349886.00	800460.40	202690.50	-202062.50	628.00	1.71	6.19	0.5791
0.091	1358710.00	796753.70	215221.20	-224704.40	-9483.19	1.71	5.35	0.5843
0.092	1367064.00	793037.10	227287.80	-247125.10	-19835.31	1.36	4.61	0.5895
0.093	1374948.00	789311.40	238901.50	-269324.00	-30422.50	0.66	4.06	0.5947
0.095	1382352.00	785570.80	250045.10	-291300.60	-41254.50	0.30	3.77	0.5999
0.096	1389287.00	781818.40	260735.50	-313055.00	-52319.50	0.30	3.64	0.6051
0.097	1395759.00	778062.00	270760.90	-334585.50	-63625.63	0.27	3.52	0.6102
0.098	1401773.00	774302.60	280735.30	-355095.00	-75159.69	0.27	3.37	0.61[illegible]

CHAPTER 6
CONCLUSIONS

6.1 Summary

This study has arisen out of a concern on the part of the public and of regulators that utilities may be incurring excessive costs for reliability. On the other hand, these groups have also expressed interest in the fact that currently, utilities are cutting deeply into their construction programs as they seek to curb expenditures. If present trends continue, the reliability of electric services could be severely jeopardized in the early 1990s. The key contribution of economic analysis to the debate is that the cost of reliability is significant, requiring decision makers to choose prices and capacity so as to balance additional benefits against additional costs of reliability.

The estimation of reliability benefits (avoided outage costs) and supply costs is necessary for a full application of the reliability optimization model. Instead of trying to capture both benefit and cost sides of alternative reliability levels, this study sharpens our understanding of the cost of reliability improves and our knowledge about the implications of alternative reliability indices for decision-making.

This study differs from previous economic studies in three respects. The first is that the reliability of power supply becomes an essential variable in the analysis of electricity costs. Two reliability indices widely used by engineers, LOLP and ε(DNS), are analyzed and constructed. The second contribution of this study is that demand and supply are both treated as stochastic variables. Most previous studies have considered "demand" as the only stochastic element, which limits the applicability of their analytical results. The third aspect of the study warranting some attention is its use of pseudo data. The numbers allow us to explore how econometric estimation techniques (and model specification) affect estimates of the cost of reliability.

In Chapter 3 we provided definitions and analyzed implications of alternative reliability indices. Then the cost characteristics of the utility industry were reviewed to facilitate the development of the model. Each of the indices was shown to have its own strengths and weaknesses; none alone provide a complete characterization of outage patterns nor of the value of lost consumption. The estimated indices are only significant in relative rather than absolute terms. Since the indices are generally neither comparable nor consistent, they yield different rankings of systems by reliability.

Due to lack of sufficient and reliable data, pseudo data based on underlying engineering and economic considerations were used in this study. In Chapter 4, we presented a simulation model to generate pseudo data. We then used alternative regression models to estimate the cost of reliability in Chapter 5.

The model we proposed is a set of two equations for reliability cost. The explanatory variables in the cost equations are total electricity consumption and a reliability index. Peak load is the only explanatory variable in the reliability equation. We separately estimated both linear and logarithmic models for each of four capacity mixes. The two-stage least-square method was used to estimate these equations.

A new concept, reliability elasticity of cost, was introduced to measure the sensitivity of cost to reliability. Those estimated elasticities shown in Table 5-1 are all much less than unity. Also, analysis of standard errors of estimated coefficients indicates that the ε(DNS) index model gives the best estimate. This result also holds for the marginal cost of electricity production.

6.2 Research Recommendations

As discussed previously, the estimation of reliability benefits (avoided outage cost) and supply cost is the prerequisite to applying the reliability optimization model. However, we only address the cost side of reliability in this study. As to the benefit side, very little hard evidence exists in economic literature. Thus, the problem of reliability benefit is a key topic for future research.

In addition, load management techniques can be used to assure that peak period demand is within the capacity limit. Two promising innovative load management practices are peak load pricing and interruptible service contracts. The former has been throughly examined in the economic literature. The results presented here show that higher peak prices increase observed reliability, and can reduce capacity requirements. The latter is relatively unexplored. Thus, it, too, is worthy of further research. The essence of interruptible service pricing is that the utility has the option of curtailing delivery of electricity in a predetermined order when available supply falls short of demand. The customers are charged different prices depending on their position in this priority ordering. Also, by virtue of their position, they confront different reliabilities of service, and the influence of these reliabilities on demand can be taken into account by system planners.

Finally, one worthwhile point for future research is that public utility commissions, environmentalists, and various citizen groups are asking electric utilities to build smaller generating units than those built in the past. They suggest that a higher reliability of a "portfolio" of smaller units would result in a reduction in generating capacity requirements, which could result in investment savings that offset the loss of economies of scale from having large units. However, others argue that the premise of economies of scale is still alive, implying that large units are more economical than smaller ones. This controversial issue also warrants further investigation. The results presented here are offered as first steps in more applications-oriented analyses of utility pricing and investment policies.

LIST OF REFERENCES

Anderson, D. "Models for Determining Least-Cost Investments in Electricity Supply," Bell Journal of Economics, Vol. 3 (Spring 1972), pp. 267-299.

Billington, R. Power System Reliability Evaluation. New York: Gordon and Breach Science Publishers, (1970).

Brown, G., and Johnson, B. M. "Public Utility Pricing and Output Under Risk," American Economic Review, Vol. 59 (March 1969), pp. 119-128.

Brown, G., and Johnson, B. M. "Public Utility Pricing and Output Under Risk; Reply," American Economic Review, Vol. 60 (June 1970), pp. 489-490.

Cargill, T. E., and Meyer, R. A. "Estimating the Demand for Electricity by Time of Day," Applied Economics, Vol. 3 (December 1971), pp. 233-246.

Chao, H. "Peak Load Pricing and Capacity Planning with Demand and Supply Uncertainty," Bell Journal of Economics, Vol. 14 (Spring 1983), pp. 119-190.

Crew, M. A., and Kleindorfer, P. R. "Reliability and Public Utility Pricing," American Economic Review, Vol. 68 (March 1978), pp. 31-40.

Crew, M. A., and Kleindorfer, P. R. "Some Elementary Considerations of Reliability and Regulation," in Problems in Public Utility Economics and Regulation. Michael A. Crew, editor. Lexington, MA: Lexington Books, (1979).

Crew, M. A., and Kleindorfer, P. R. "Electricity Pricing and Plant Mix Under Supply and Demand Uncertainty," in Regulatory Reform and Public Utilities. Michael A. Crew, editor. Lexington, MA: Lexington Books, (1982).

Endrenyi, J. Reliability Modeling in Electric Power Systems. New York: John Wiley and Sons, (1978).

Electric Power Research Institute Workshop Report, "Workshop Proceedings: Power System Reliability--Research Needs and Priorities," Electric Power Research Institute, (1978).

Electric Power Research Institute Workshop Report, "Workshop Proceedings: Environmental and Social Impacts of an Electricity Shortage," Electric Power Research Institute, (June 1978).

Florida Electric Power Coordinating Group, Inc., "Peninsular Florida Generation Reliability Study, 1978-1987," Florida Electric Power Coordinating Group, (1978).

Garver, L. L., and Moison, R. W. "Calculation Procedure for Loss of Load Probability," Working Paper, General Electric Company, (1972).

George, A., and Batavia, B. N. "Estimation of a Frontier Production Function for Steam Power Generation," 52nd Annual Western Economic Association Conference, DePaul University, (1979).

Gerber, A. "The Issue of Reliability," Public Utilities Fortnightly, Vol. 101 (April 12, 1979), pp. 23-26.

Griffen, J. M. "Long-Run Production Modeling with Pseudo Data: Electric Power Generation, Bell Journal of Economics, Vol. 8 (Spring 1977), pp. 112-127.

Kmenta, J. Elements of Econometrics. New York: Macmillan Publishing Company, (1971).

Kendrick, J. W. "Efficiency Incentives and Cost Factors in Public Utility Automatic Revenue Adjustment Clauses," Bell Journal of Economics, Vol. 6 (Spring 1975), pp. 299-313.

Maddala, G. S., Chern, W., and Gill, G. Econometric Studies in Energy Demand and Supply. New York: Praeger Publishers, (1978).

Maddala, G. S., and Roberts, B. R. "Statistical Cost Analysis Revisited," Quarterly Journal of Economics, Vol. 96 (February 1981), pp. 177-180.

Mather, N. "The Determinants of Electricity Distribution Costs in the U.S. and Canada," Wayne Economic Papers, (May 1977).

Meyer, R. "Cost Structures and Multifacility Capacity: Applications to Some Electric Energy Policy Issues," Journal of Economics and Business, Vol. 31 (Fall 1978), pp. 57-62.

Meyer, R. "Monopoly Pricing and Capacity Choice Under Uncertainty," American Economic Review, Vol. 65 (June 1975), pp. 326-337.

Munasinghe, M. The Economics of Power System Reliability and Planning: Theory and Case Study. Baltimore: Johns Hopkins University Press, (1979).

Munasinghe, M., and Gellerson, M. "Economic Criteria for Optimizing Power System Reliability Levels," Bell Journal of Economics, Vol. 10 (Spring 1979), pp. 353-365.

Nguyen, D. T. "Public Utility Pricing with Stochastic Demand: A Note," Applied Economics, Vol. 10 (March 1978), pp. 43-47.

Platts, J. E., and Womeldorff, P. J. "The Significance of Assumptions Implied in Long-Range Electric Utility Planning Studies," Power Engineering Society, Institute of Electrical and Electronic Engineers, Northeast Utilities and Illinois Power Company, (1978).

Rowse, J. "Intertemporal Pricing and Investment for Electric Power Supply," Bell Journal of Economics, Vol. 11 (Spring 1980), pp. 143-165.

Salkever, D. "Public Utility Pricing and Output Under Risk: Comment," American Economic Review, Vol. 60 (June 1970), pp. 487-488.

Sant, D. "The Implication of Prices for Load Management in Electric Power Generation," Southern Economic Journal, Vol. 45 (January 1979), pp. 743-759.

Sherman, R., and Visscher, M. "Second-Best Pricing with Stochastic Demand," American Economic Review, Vol. 68 (March 1978), pp. 41-53.

Smith, K. V., and Vaughan, W. J. "Some Limitations of Long-Run Production Modeling with Pseudo Data," Journal of Industrial Economics, Vol. 18 (December 1979), pp. 201-207.

Sommers, P. "The Adoption of Nuclear Power Generation," Bell Journal of Economics, Vol. 11 (Spring 1980), pp. 283-292.

Sullivan, R. L. Power System Planning. New York: McGraw-Hill, (1977).

Sullivan, R. L. "Worth of Reliability," Working Paper, Department of Electrical Engineering, University of Florida, (1980).

Sullivan, R. L. "Evaluating Reliability and Operating Cost Impacts of Time of Use Rates," in Innovative Electric Rates. Sanford V. Berg, editor. Lexington, MA: Lexington Books, (1983).

Taylor, L. "The Demand for Electricity: A Survey," Bell Journal of Economics, Vol. 6 (Spring 1975), pp. 74-110.

Telson, M. "The Economics of Alternative Levels of Reliability for Electric Power Generation Systems," Bell Journal of Economics, Vol. 6 (Autumn 1975), pp. 679-694.

Tschirhart, J. "On Public Utility Pricing under Stochastic Demand," Working Paper, Department of Economics, University of Wyoming, (1978).

Tschirhart, J. "Towards Optimum Load Management," Working Paper, Department of Economics, University of Wyoming, (1980).

Tschirhart, J., and Jen, F. "Behavior of a Monopoly Offering Interruptible Service," Bell Journal of Economics, Vol. 10 (Spring 1979), pp. 244-258.

Turvey, R. "Public Utility Pricing and Output Under Risk: Comment," American Economic Review, Vol. 60 (June 1970), pp. 485-486.

Turvey, R., and Anderson, D. Electricity Economics. Baltimore: Johns Hopkins University Press, (1977).

United Nations, "Problems of Meeting Peak Electricity Demands: A General Study," Department of Economic and Social Affairs, United Nations, (1973).

Webb, M. "The Determination of Reserve Generating Capacity Criteria in Electricity Supply Systems," Applied Economics, Vol. 9 (March 1977), pp. 19-31.

Williams, P. "Taking Another Look at Electrical System Reliability," Public Utilities Fortnightly, Vol. 99 (March 17, 1977), pp. 23-26.

Wolff, R. "New Reliability Index Challenges LOLP," Electrical World, Vol. 198 (September 15, 1979), pp. 124-128.

BIOGRAPHICAL SKETCH

Shukuang Jen was born May 29, 1944, in Szechuan, China. His undergraduate education was received at the National Cheng Chi University in Taiwan, China. In 1972, he attended the University of Florida in Gainesville, Florida, where he received a Master of Business Administration degree in accounting in 1973. In 1976, he returned to the University of Florida to continue his graduate work and subsequently was granted an M.A. degree in economics in 1979. A doctoral degree is expected from the University of Florida in August 1983.

I certify that I have read this study and that in my opinion it conforms to acceptable standards of scholarly presentation and is fully adequate, in scope and quality, as a dissertation for the degree of Doctor of Philosophy.

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